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Dermatology Chatbot: An AI-Driven Solution for Accessible Skin Care

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Abstract

The emergence of chatbots in the healthcare sector is increasingly pivotal, as they provide rapid and accessible assistance for the early detection of diseases and medical guidance. This study delineates a sophisticated two-tier healthcare chatbot system that synergistically integrates deep learning for image-based skin disease classification with machine learning for symptom-driven disease prediction. The system, developed in Python, employs a Hybrid U-Net & Improved MobileNet-V3 model to accurately identify dermatological conditions from images, while a Decision Tree Classifier is utilized to forecast diseases based on user-reported symptoms. Through meticulous evaluation of user inputs, the chatbot facilitates interactive consultations that encompass severity assessments, disease predictions, and preventive recommendations. Rigorous cross-validation of the symptom-based models, alongside testing on a bespoke dataset of skin disease images, substantiates the efficacy of the proposed methodology, demonstrating commendable predictive accuracy. The chatbot exemplifies significant potential by amalgamating conversational artificial intelligence with a hybrid approach of Hybrid U-Net & Improved MobileNet-V3 for image classification and Decision Tree Classifier for symptom analysis, thereby enhancing the landscape of telemedicine and patient care.

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1. Introduction

The integration of advanced CNN architectures has significantly improved the classification performance of skin lesions, achieving accuracies of 89.71% on the HAM10000 dataset and 88.57% on the Dermnet dataset, demonstrating the potential of AI in clinical diagnosis [1]. shown that deep learning models can classify skin cancer with accuracy comparable to that of dermatologists, highlighting the revolutionary effects of AI in dermatology. The implementation of chatbots in dermatology signifies a ground-breaking advancement in patient care, particularly in the accurate diagnosis of skin conditions, by harnessing the latest developments in artificial intelligence (AI) and machine learning (ML)[2]. Given the wide spectrum of dermatological issues, which can range from benign irritations to life-threatening disorders, timely and precise diagnosis is paramount to mitigate potential complications. Traditional diagnostic methodologies often fall short due to the intricate nature of skin conditions, variability in clinical presentation, and a pronounced scarcity of specialists, especially in underserved regions [3].

This challenge is adeptly addressed through the integration of AI-powered conversational agents that facilitate early detection and personalized treatment recommendations via effective user interactions. One innovative approach involves the design of multimodal systems that amalgamate image processing and natural language processing (NLP) through chatbot interfaces. For instance, chatbots can employ Hybrid U-Net & Improved MobileNet-V3, a sophisticated model for image classification, alongside Convolutional Neural Networks (CNNs) to accurately classify skin diseases, while simultaneously utilizing NLP to elicit detailed symptom descriptions from users, thereby enriching the diagnostic context [4]. Systems such as "Dermatobot" exemplify this integration, combining text analysis with image analysis to recommend treatments for identified conditions. Additionally, the incorporation of reinforcement learning techniques has been shown to enhance the adaptability and responsiveness of these chatbots, further improving user engagement and diagnostic accuracy. Furthermore, recent studies underscore the efficacy of these chatbots, revealing their capacity to classify symptoms and detect diseases with remarkable accuracy, often achieving levels exceeding 90% during real-time consultations [5]. However, it is crucial to recognize that these systems serve as supplementary tools and should not supplant expert medical advice. In conclusion, the deployment of chatbots in dermatology signifies a pioneering stride towards enhancing the efficiency and accessibility of healthcare services, ultimately fostering improved patient outcomes in this critical domain.

2. Related works

The integration of computer vision and natural language processing (NLP) within AI-powered healthcare chatbots has emerged as a promising frontier in enhancing dermatological care. Numerous research studies have scrutinized the efficacy of these technologies in delivering convenient, real-time consultations for skin-related concerns. A notable instance of such an AI-driven chatbot is Dermatobot. This innovative system facilitates the identification of skin conditions and the recommendation of treatments by employing Hybrid U-Net & Improved MobileNet-V3 for semantic similarity evaluations in conjunction with the Universal Sentence Encoder for image classification. Furthermore, Dermatobot enhances accessibility to dermatological care through an intuitive interface, enabling patients to receive immediate assistance and acquire knowledge about their ailments [6].

Multiple studies have evaluated the effectiveness of AI chatbots in the realm of dermatology. A specific research study underscores the significance of chatbots in patient education, accentuating their potential for early disease identification and treatment recommendations [7], [8]. However, this study positions these systems as supplementary resources rather than primary diagnostic tools, thereby highlighting their limitations in generating precise and reliable diagnoses. Supporting this assertion, another investigation that assesses the clinical accuracy of responses from various AI models, including Microsoft Copilot and ChatGPT, reveals encouraging findings. While these models exhibit potential in addressing dermatological inquiries, they also underscore the necessity for further advancements in diagnostic accuracy [9], [10], [11].

A comprehensive review delves into the development of DermCDSM, a clinical decision support model designed to leverage a hybrid deep learning approach for the early detection and classification of skin diseases. This model amalgamates Convolutional Deep Spiking Neural Networks (CD-SNN) with an enhanced Chameleon Swarm Optimization (ICSO) algorithm for sophisticated segmentation and feature selection. Validation using the ISIC 2017 dataset demonstrates superior performance compared to existing methodologies, thereby underscoring the model's robustness and diagnostic efficacy in skin disease classification [12]. The reliance on deep learning, particularly Convolutional Neural Networks (CNNs), for skin lesion classification and segmentation is further examined in a study. This research emphasizes the critical role of extensive datasets in training CNNs effectively. By delineating pre-processing techniques aimed at augmenting image analysis accuracy, the paper elucidates how deep learning models can be harnessed to categorize skin lesions through the extraction of intricate patterns from dermatological images [13]

Moreover, another article discusses the utility of CNNs and other specialized architectures tailored for dermatological diagnostics, accentuating the importance of pre-processing and the utilization of existing datasets in enhancing model performance. Despite significant advancements, the study notes that achieving high accuracy remains a formidable challenge due to variations in image quality and the diverse characteristics of skin diseases [14]. A more recent approach addresses segmentation challenges arising from data uncertainty in skin lesion analysis by integrating CNNs with deep hyperspherical clustering. The incorporation of a unique hypersphere loss function significantly mitigates the dependence on labelled data, thereby enhancing model training. Experiments conducted on various benchmark datasets reveal improved segmentation performance. Collectively, these studies illustrate the burgeoning application of AI technologies in dermatology, with a focus on augmenting patient interaction, enhancing diagnostic accuracy, and providing effective medical solutions. While the advancements in these systems have yielded promising results, there remains substantial scope for improvement, particularly concerning the clinical precision of diagnoses, which continues to pose a significant obstacle within the field.

3. Performance Evaluation of Proposed Method

The user initiates the diagnostic process by inputting symptoms through the chatbot interface, which is meticulously designed to structure and aggregate the provided data for further analysis. Subsequently, the validation module rigorously scrutinizes the input for accuracy and completeness, mitigating inconsistencies and minimizing the likelihood of erroneous data. Once validated, the data undergoes sophisticated computational analysis within the processing unit, which leverages advanced machine learning algorithms to cross-reference symptoms against an extensive medical knowledge base. This facilitates the generation of highly accurate disease predictions and severity assessments.. Finally, the output module articulates the analytical findings in a clear and comprehensible manner, providing users with potential diagnoses, severity classifications, and precautionary measures. Additionally, it proactively recommends medical consultation when necessary, ensuring a holistic and informed approach to healthcare decision-making.

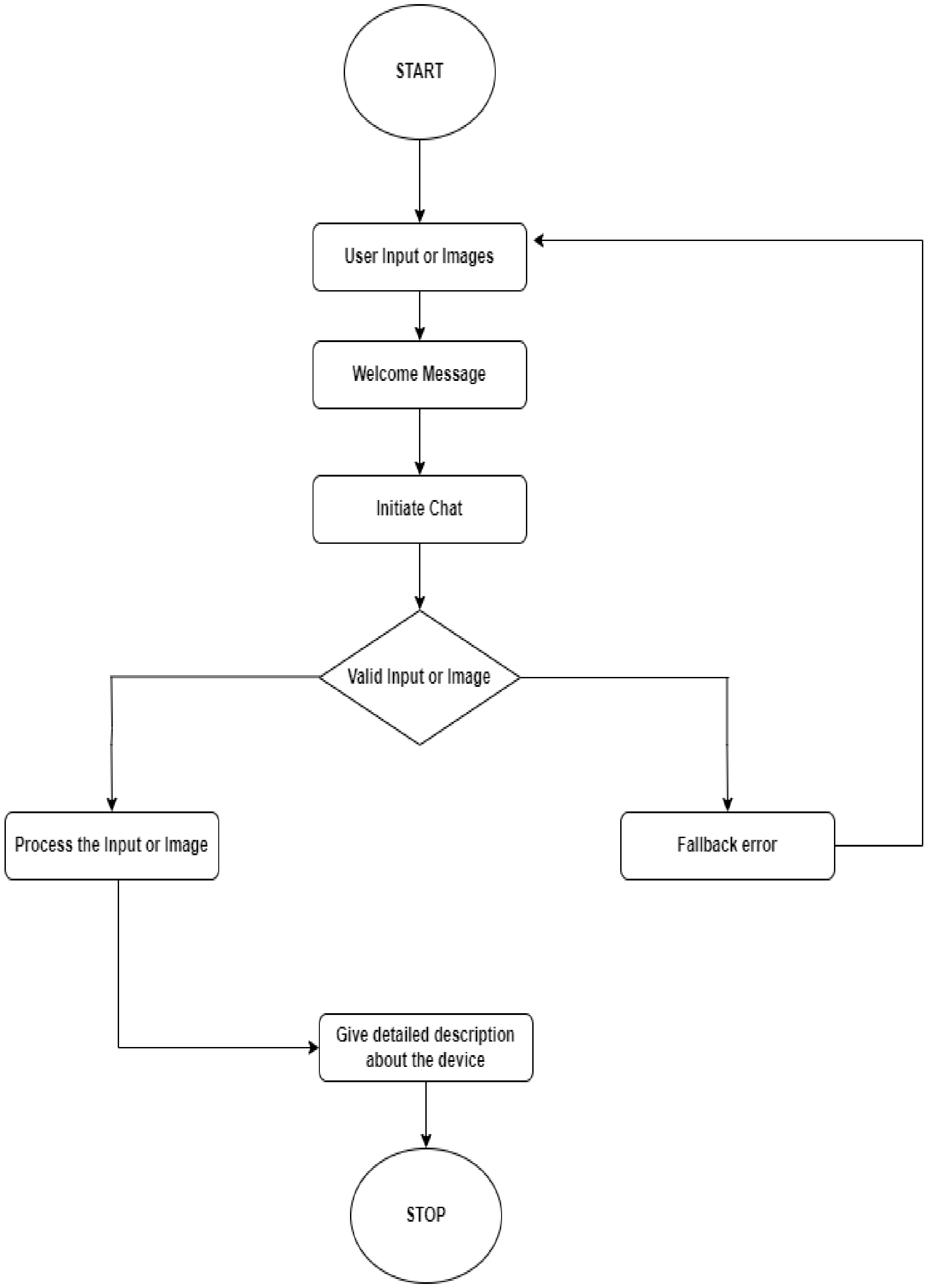

Figure 1: Illustrative representation of the Hybrid Net and MobileNet v3.

Figure 1 represents the Hybrid Net and MobileNet v3 where the foundation of the AI-powered disease detection system is built upon a meticulously structured, multi-component framework aimed at enhancing diagnostic precision, user accessibility, and operational efficiency. As the prevalence of digital healthcare solutions continues to rise, the need for an intelligent, automated diagnostic system that minimizes human error and expedites the medical assessment process has become increasingly apparent. The system is designed to integrate cutting-edge artificial intelligence techniques with user-friendly interfaces to facilitate seamless interactions and provide accurate, data-driven health insights.

Central to this system is the user, who serves as the primary initiator of the diagnostic process by submitting medical data in the form of textual symptom descriptions or images. This multi-format input capability ensures that individuals from diverse demographic and technological backgrounds can access and utilize the system effectively, regardless of their preferred mode of interaction. By accommodating both text-based and image-based input, the system increases its versatility and broadens its applicability to a wide range of medical conditions. To initiate the process, the user engages with a chatbot interface, which has been designed to provide an intuitive, guided experience. This interface plays a crucial role in structuring user-provided information while maintaining a smooth conversational flow, ensuring that users receive appropriate guidance at every step. Additionally, it responds to frequently asked questions, offers preparatory advice on input submission, and clarifies ambiguities in symptom descriptions, thereby improving the accuracy of the diagnostic process.

Upon the receipt of input, the validation module assumes a critical role in assessing the quality and relevance of the submitted information. This module is designed to ensure that all input data adhere to predefined standards of completeness, clarity, and format suitability. Any incomplete, ambiguous, or improperly formatted data is flagged, prompting the system to request corrections from the user before proceeding to the next phase. This rigorous validation mechanism serves as a safeguard against erroneous or misleading data that could compromise diagnostic accuracy. Additionally, the validation module performs preliminary pre-processing tasks, such as enhancing image clarity through noise reduction and optimizing textual descriptions by applying natural language processing techniques. These preparatory steps are essential in facilitating an accurate and efficient analysis during subsequent processing stages.

Following successful validation, the processing unit employs state-of-the-art computational methodologies to extract relevant medical insights from the input data. When image-based input is provided, advanced computer vision algorithms analyse the image for patterns indicative of various medical conditions, utilizing pre-trained deep learning models to detect abnormalities and classify potential diseases. In cases where textual descriptions serve as input, Natural Language Processing (NLP) algorithms are deployed to parse the information, identify key symptoms, and cross-reference them against an extensive medical knowledge base. Through a combination of machine learning-driven pattern recognition and statistical analysis, the system synthesizes the collected data and generates preliminary diagnostic assessments. Over time, the processing unit refines its predictive accuracy by leveraging historical data, continuously improving its capacity to detect emerging trends and correlations between symptoms and medical conditions.

The final stage of the diagnostic process occurs in the output module, where the system presents its findings in a clear and comprehensible format. This module is responsible for generating structured reports that summarize the system's diagnostic conclusions, including predicted diseases, severity levels, and precautionary measures. Additionally, the output module provides recommendations on further medical action, such as scheduling an appointment with healthcare professional or undergoing specific medical tests for confirmation. The system is also equipped with interactive follow-up functionalities, enabling users to seek further clarification, request additional analyses, or obtain referrals to nearby medical institutions when necessary. By ensuring that diagnostic insights are communicated effectively and accompanied by actionable recommendations, In order to bridge the gap between initial self-assessment and expert medical consultation, the output module is essential.

Beyond its immediate diagnostic capabilities, this AI-powered disease detection system is designed to be dynamic, scalable, and continuously evolving. The modular architecture of the system allows for seamless integration of increasingly sophisticated artificial intelligence models, thereby expanding the range of detectable conditions and improving diagnostic precision. As machine-learning algorithms are exposed to larger datasets over time, their predictive accuracy is expected to improve, enhancing the system's ability to recognize rare and complex medical conditions. Furthermore, as advancements in AI and computational medicine progress, the system's adaptability ensures that it remains at the forefront of medical innovation.

By synthesizing rigorous validation mechanisms, advanced analytical processing, and an intuitive user interface, this system empowers individuals with timely and data-driven health insights. It fosters a proactive approach to healthcare by enabling users to make informed decisions about their well-being while simultaneously reducing the burden on medical professionals by filtering out non-critical cases. As a result, this AI-driven framework not only enhances accessibility to preliminary medical assessments but also contributes to the broader objective of improving healthcare efficiency and diagnostic reliability in the digital age.

Progression of the Method

The medical specialty of dermatology is devoted to the diagnosis and treatment of disorders affecting the skin, hair, and nails. In India, pursuing a career in dermatology necessitates the completion of a three-year postgraduate program following the attainment of a Bachelor of Medicine and Bachelor of Surgery (MBBS) degree, underscoring the critical role dermatologists play in both research and clinical practice. Specialization opportunities include postgraduate diplomas, Master of Science (MS), or Doctor of Medicine (MD) degrees. Given that skin disorders can affect individuals across all age groups, early recognition and treatment are paramount to enhancing patient outcomes, minimizing scarring, and expediting recovery. However, dermatologists remain scarce, particularly in rural regions, thereby necessitating the integration of AI-driven chatbots for the efficient diagnosis and management of dermatological conditions.

Understanding skin types is essential in dermatology, as it informs the selection of appropriate skincare and treatment regimens. Human skin is typically categorized into four primary types: oily, dry, combination, and normal. Oily skin is characterized by excessive sebum production, leading to acne and clogged pores, while dry skin results from insufficient sebum production, manifesting as tightness, flakiness, and irritation. Combination skin exhibits both dry and oily characteristics, often presenting dry cheeks alongside an oily T-zone. Normal skin appears healthy and resilient, with balanced sebum and moisture levels. Additionally, sensitive skin is recognized as a subtype that is more prone to irritation from skincare products, thereby increasing the likelihood of developing various skin conditions. The integration of chatbots in dermatology significantly enhances accessibility and efficiency in skincare management. By providing prompt responses, these AI-powered solutions substantially reduce the frequency of doctor visits, thereby conserving both time and financial resources. Their scalability is further assured by the capacity to handle multiple inquiries simultaneously, rendering dermatological assistance readily available, particularly in geographically isolated areas. Moreover, chatbots serve as educational tools, imparting valuable information regarding skin diseases and available treatment options. Nevertheless, several limitations persist despite these advantages. One of the primary concerns is emotional sensitivity; chatbots may struggle to comprehend human emotions, potentially leading to user dissatisfaction. Interactions can feel less personalized due to the occasionally repetitive and contextually inflexible responses generated by these systems.

As advancements in digital health continue to proliferate, numerous AI-powered chatbots have been developed to assist individuals with skin issues. A notable example is the Melanoma Check Chatbot, which employs the ABCDE criteria—Asymmetry, Border irregularity, Colour variation, Diameter, and Evolution—to evaluate skin lesions and assess risk factors associated with dark spots or moles. While these AI-driven assessments provide preliminary guidance, a professional evaluation, often necessitating a biopsy, remains essential for a definitive diagnosis. Research indicates that convolutional neural networks (CNNs) have significantly enhanced diagnostic accuracy in differentiating between benign and malignant lesions. Another noteworthy AI-powered tool is the Acne Bot, which aids individuals in managing acne by offering personalized skincare routines, lifestyle recommendations, and treatment options based on the location and severity of their acne. The application of machine learning classifiers to distinguish between various skin lesions has gained traction, with profound implications for acne treatment.

The utilization of image-based analysis in dermatology chatbots has also surged as AI technology advances. By leveraging extensive datasets such as HAM10000, which comprises a diverse collection of annotated dermatoscopic images, and DermNet, a comprehensive online resource for dermatological information, these intelligent chatbots enable users to upload images of their skin concerns for analysis. These datasets are instrumental in training AI models to recognize and classify various skin conditions accurately. Furthermore, the integration of large-scale datasets enhances the robustness of AI algorithms, allowing for improved generalization across diverse populations and skin types. However, researchers emphasize the critical importance of interpretability in AI models, particularly within medical contexts. Explainable AI frameworks are vital for ensuring that both users and healthcare professionals can comprehend the rationale behind AI-driven diagnoses, thereby maintaining transparency and trust in this systems.The intersection of dermatology and AI presents promising solutions for enhancing skincare accessibility, particularly in underserved areas. While chatbots offer efficiency, user-friendliness, and educational support, their reliance on high-quality data and inability to replicate human emotional intelligence highlight the need for ongoing refinement. As technology continues to evolve, the application of AI in dermatology is expected to advance, yielding more precise, personalized, and accessible skin health management solutions.

Proposed: Hybrid u-net & improved mobilenet-v3

The proposed approach establishes a robust dermatological healthcare assistant by integrating advanced deep learning models, rule-based diagnostic procedures, and machine learning techniques. This multifaceted method leverages the latest advancements in artificial intelligence and image processing to address critical challenges such as diagnostic accuracy, interpretability, and scalability. The system is meticulously designed with two primary components: a symptom-based diagnostic chatbot and an image-based deep learning classifier, thereby ensuring comprehensive diagnostic support for skin ailments.

The first component is a rule-based chatbot that employs a Decision Tree Classifier to evaluate symptoms reported by users. Through an intuitive conversational interface, users articulate their symptoms to the chatbot. To identify relevant symptoms, the chatbot meticulously analyzes these inputs using regular expressions and pattern matching techniques. These symptoms are subsequently mapped to a cumulative severity score utilizing a severity lexicon. The system is programmed to recommend that users seek professional medical assistance if this score exceeds a predetermined threshold. The Decision Tree Classifier enhances interpretability in structured diagnostic procedures by predicting potential illnesses based on labeled symptom-disease data. Research underscores the efficacy of decision trees in improving the precision of diagnosing skin conditions, thereby reaffirming their utility in medical settings.

The second component employs an Hybrid U-Net & Improved MobileNet-V3-based Convolutional Neural Network (CNN) to identify skin conditions based on user-uploaded photographs. Hybrid U-Net & Improved MobileNet-V3, known for its state-of-the-art performance in image classification tasks, optimizes both accuracy and computational efficiency by scaling up the network width, depth, and resolution in a balanced manner. This architecture has demonstrated remarkable effectiveness in differentiating between benign and malignant skin conditions, achieving accuracy levels comparable to those of licensed dermatologists. To enhance model generalizability, pre-processing techniques such as rescaling, shearing, zooming, and horizontal flipping are incorporated into the training dataset. The Hybrid U-Net & Improved MobileNet-V3 architecture comprises dense layers for classification, max-pooling layers for dimensionality reduction, a dropout layer to mitigate overfitting, and multiple convolutional layers for feature extraction. Results indicate that the model can accurately identify up to 23 distinct skin disorders, surpassing traditional classification techniques. Performance metrics, including accuracy and loss, are meticulously monitored throughout the training process.

To bolster usability and trust, the system integrates Explainable AI (XAI) methodologies. The symptom-based approach enhances diagnostic transparency by elucidating significant contributing symptoms and their corresponding severity scores. Furthermore, to ensure improved interpretability, the Hybrid U-Net & Improved MobileNet-V3 model employs Grad-CAM (Gradient-weighted Class Activation Mapping) to visualize the specific areas of the skin image that influenced the model's decision-making process. These explain ability features effectively address the increasing demand for transparent AI applications, particularly in high-stakes domains such as dermatological diagnostics.

The system delivers comprehensive diagnostic outputs, including probable illnesses, preventive measures sourced from a precautionary database, and detailed explanations of diseases derived from a symptom description dictionary. By amalgamating rule-based and deep learning techniques, the proposed method significantly enhances the precision, interpretability, and user confidence in AI-assisted dermatological diagnosis. This hybrid strategy represents a substantial advancement in the automation and enhancement of dermatological healthcare delivery.

Moreover, the proposed method incorporates advanced coding techniques to facilitate seamless integration of the various components. The implementation of the Decision Tree Classifier and Hybrid U-Net & Improved MobileNet-V3 is executed using Python, leveraging libraries such as TensorFlow and Scikit-learn for model training and evaluation. The coding framework is designed to ensure modularity, allowing for easy updates and enhancements as new data becomes available. This approach not only addresses existing limitations in machine learning-based diagnostics but also offers a scalable and reliable solution for early disease identification and management.

In alignment with contemporary dermatology, initiatives aimed at improving healthcare automation, accessibility, and diagnostic accuracy, this strategy positions itself as a pivotal contribution to the field. By integrating cutting-edge machine learning and deep learning techniques, the proposed approach is poised to revolutionize the landscape of dermatological diagnostics, ultimately leading to better patient outcomes and enhanced healthcare delivery. Furthermore, the incorporation of Hybrid U-Net & Improved MobileNet-V3 not only enhances the model's performance but also reduces the computational resources required for training and inference, making it a practical choice for deployment in real-world applications.

Protocol Design

Effective algorithms prioritize accuracy, efficiency, and scalability to optimize performance across various applications.

Algorithm 1 Disease prediction

Step 1: Load training and testing datasets.

Step 2: Encode categorical symptom labels into numerical values using Label Encoding.

Step 3: Split dataset into training and testing subsets.

Step 4: Train classifiers (Decision Tree, SVM) on training data.

Step 5: Perform cross-validation and compute accuracy scores.

Step 6: Load severity levels, symptom descriptions, and precautionary measures.

Step 7: Initialize Q = Capture user details (name, symptoms, duration).

Step 8: i = 0

Step 9: while i >= 0 do

Step 10: for each symptom in user input do

Step 11: Search for pattern matches in predefined symptom list.

Step 12: If no match found, request user to re-enter valid symptom.

Step 13: If match found, validate symptom through secondary confirmation.

Step 14: Predict probable disease using Decision Tree model.

Step 15: If confidence is low, perform an alternative classification.

Step 16: Display predicted disease, medical details, and recommended precautions.

Step 17: Store identified symptoms for further analysis.

Step 18: end for

Step 19: i = i - 1

Step 20: end while

Step 21: Return (Q).

The proposed Algorithm 1 Disease Prediction systematically processes patient-reported symptoms to facilitate Disease prediction through a structured machine-learning pipeline. Initially, training and testing datasets are acquired and pre-processed to ensure data integrity and feature standardization. Categorical symptom variables are numerically encoded using Label Encoding, enabling compatibility with supervised learning models. The dataset is then partitioned into training and testing subsets to optimize model generalizability. Machine learning classifiers, including Decision Trees and Support Vector Machines (SVM), are trained to develop a robust predictive framework, with cross-validation employed to assess model reliability and accuracy. To enhance diagnostic precision, a medical knowledge base is integrated, incorporating symptom severity indices, disease descriptions, and precautionary measures. During user interaction, the system initializes a query session (Q) to collect patient details, including demographic information, symptoms, and duration. The core computational process is structured as an iterative loop, wherein each reported symptom undergoes pattern matching against a predefined medical database. If no match is detected, the user is prompted for re-entry; otherwise, symptom validation proceeds through a secondary confirmation stage. Probable diseases are then predicted using the trained Decision Tree model, with an alternative classifier employed in cases of low confidence. The system subsequently presents the predicted disease, relevant medical insights, and precautionary recommendations while storing identified symptoms for potential further analysis. This structured approach ensures a balance between machine learning-driven diagnostics and medically validated contextualization, thereby enhancing the system's reliability and applicability in clinical settings.

The integration of a medical knowledge base is particularly crucial, as it allows for the incorporation of expert clinical insights into the machine-learning framework, thereby improving the overall diagnostic accuracy. This aligns with findings that emphasize the importance of combining AI-driven models with established medical knowledge to enhance decision-making processes in healthcare [25]. Furthermore, the iterative loop for symptom validation reflects best practices in clinical decision support systems, ensuring that user inputs are rigorously checked against established medical criteria [26].

Algorithm 2 Training the Image

Step 1: Import TensorFlow and required libraries for deep learning and data pre-processing.

Step 2: Define dataset paths for training and testing images.

Step 3: Set image dimensions and model hyperparameters (batch size, epochs, and number of classes).

Step 4: Initialize ImageDataGenerator for data augmentation and normalization.

Step 5: Load images from directories and pre-process them into batches.

Step 6: Initialize Q = Create CNN model using Hybrid U-Net & Improved MobileNet-V3V2 as the base, followed by pooling and dense layers.

Step 7: Compile the model using Adam optimizer and categorical cross-entropy loss.

Step 8: i = 0

Step 9: while i < epochs do

Step 10: Train model using training data generator.

Step 11: Validate model performance on the test dataset after each epoch.

Step 12: If validation accuracy improves, continue training; else, adjust parameters.

Step 13: Save the trained model for future inference.

Step 14: end while

Step 15: Initialize Q = Generate accuracy and loss plots for training history.

Step 16: Display accuracy and loss curves to analyze model performance.

Step 17: Return (Q).

The Algorithm 2 Image training begins by importing TensorFlow and other essential libraries required for deep learning and image pre-processing, ensuring seamless handling of image data and neural network training. The dataset paths for training and testing images are then defined, allowing structured data retrieval. Image dimensions and hyperparameters, such as batch size, number of epochs, and class count, are set to optimize computational efficiency and accuracy. To enhance generalization and mitigate overfitting, data augmentation techniques, including rescaling, shearing, zooming, and horizontal flipping, are applied using ImageDataGenerator. Images are loaded from the specified directories, reprocessed into batches, and prepared for model training. The convolutional neural network (CNN) is constructed using Hybrid U-Net & Improved MobileNet-V3V2 as the base model, leveraging its pre-trained feature extraction capabilities. A softmax output layer for multi-class classification comes after dense layers that improve feature representations and a global average-pooling layer that takes the place of conventional flattening. The Adam optimiser and categorical cross-entropy loss are then used to compile the model. Ensuring adaptive learning rate adjustments and effective error minimization. Training begins with an iterative loop where, for each epoch, the model is trained using batch-wise image input, followed by validation against a separate test dataset to assess generalization performance. If validation accuracy improves, training continues; otherwise, hyperparameters may be adjusted to enhance learning. The trained model is subsequently saved for future inference, preserving its predictive capabilities for real-world dermatological applications. Once training is complete, accuracy and loss metrics are plotted to visualize the model's learning progress, aiding in performance analysis. These graphical representations help identify trends, detect potential overfitting, and inform further refinements. The algorithm concludes by returning the trained model alongside its performance metrics, encapsulating the entire pipeline from data pre-processing to predictive analysis in a structured and interpretable manner.

Algorithm 3 Testing the Image

Step 1: Import TensorFlow and required libraries for image processing.

Step 2: Suppress TensorFlow warnings for cleaner output.

Step 3: Load the trained CNN model for skin disease classification.

Step 4: Define class labels corresponding to different skin diseases.

Step 5: Initialize function predict_disease_from_image(img_path).

Step 6: Check if the input image file exists; return an error message if not.

Step 7: Load and preprocess the input image (resize, normalize, reshape).

Step 8: Feed the preprocessed image into the model for prediction.

Step 9: Compute the predicted class index using argmax.

Step 10: Retrieve the corresponding disease label from the class list.

Step 11: Compute the confidence score of the prediction.

Step 12: Return the predicted disease name with the confidence score.

Step 13: Initialize img_path with the test image location.

Step 14: Call predict_disease_from_image(img_path).

Step 15: Print the predicted disease name and confidence score.

Step 16: Return (Q).

The Algorithm 3 Testing the image commences by importing TensorFlow along with other requisite libraries essential for image processing, ensuring a robust framework for deep learning-based classification. To enhance the clarity of the output, TensorFlow warnings are suppressed, mitigating unnecessary verbosity during execution. The pre-trained convolutional neural network (CNN) model, designed explicitly for skin disease classification, is then loaded, allowing for efficient inference on dermatological images. Subsequently, class labels corresponding to distinct skin diseases are defined, mapping numerical predictions to their respective medical conditions. The function predict_disease_from_image (img_path) is then initialized to facilitate image-based diagnosis. Before processing, the algorithm verifies whether the specified image file exists; if absent, an error message is returned to prevent disruptions in execution. Upon successful validation, the input image undergoes preprocessing, including resizing to a standardized dimension, normalization to ensure consistent pixel value distribution, and reshaping to align with the model has input format. The reprocessed image is then fed into the CNN model for inference, where predictive computations take place. The algorithm determines the most probable disease category by applying the argmax function, extracting the index of the highest probability score from the model's output. This index is used to retrieve the corresponding disease label from the predefined class list, effectively translating numerical outputs into human-interpretable medical diagnoses. Additionally, the algorithm computes the confidence score, representing the model's certainty in its prediction, and presents it as a percentage for better interpretability. The predicted disease name, along with its confidence score, is then returned as the final output. To validate the prediction pipeline, an image path is assigned to img_path, pointing to a test image intended for inference. The function predict_disease_from_image(img_path) is invoked, executing the entire prediction process. The resultant diagnosis and confidence level are then printed, providing a clear and quantifiable assessment of the model's decision. The algorithm concludes by returning Q, encapsulating the end-to-end prediction workflow in a structured and methodical manner.

4. Result and Discussion

The Decision Tree algorithm categorizes ailments based on user-provided symptoms. It constructs a decision path based on symptom severity to predict potential illnesses. The algorithm's interpretability makes it suitable for health diagnostics, allowing for a clear understanding of how predictions are made. The Gini Impurity and Entropy formulas are used to determine the best splits at each node in the tree:

Gini Impurity

$$\text{Gini}(D) = 1 - \Sigma (p_i)^2 \quad (1)$$

Where:

Σ runs from i =1to n.

Entropy

$$\text{Entropy}(D) = - \Sigma (p_i * \log_2 p_i) \quad (2)$$

Where:

Σ runs from i =1to n.

p_i is the probability of class in dataset .

To determine the best hyperplane for class separation, the Support Vector Machine (SVM) projects data points into a higher-dimensional space. The margin between the hyperplane and the support vectors is maximised. SVM is used to classify diseases based on symptoms, offering an alternative to decision trees and handling high-dimensional data well. The hyperplane equation is: $w.x + b = 0$, where w is the weight vector, x is the input vector, and b is the bias term. The objective function of the SVM maximizes the margin M while minimizing classification error: Maximize $M = 1/||w||$ subject to $yi(w.xi + b) \geq 1$ for all i.

Convolutional Neural Networks (CNNs) are used for image classification. They extract features through convolutions and pooling layers, and then use fully connected layers for classification. CNNs excel at identifying intricate patterns in images, making them suitable for classifying skin conditions. The convolution and pooling (max pooling) formulas are:

Convolution

$$I(x+i, y+j).K(i,j) \quad (3)$$

Where:

$I_{out}(x,y)$ is the output of the convolution operation

$I(x,y)$ is the input image.

$K(i,j)$ is the kernel or filter.

m and n are the dimensions of the kernel.

Pooling

$$p(x,y) = max(I(x,y), I(x+1,y), \ldots, I(x+m, y+n)) \quad (4)$$

Where:

$P(x, y)$ is the pooled value at position (x,y)

The kernel size (i,j)determines the region from which the maximum value is taken.

The Natural Language Processing (NLP) algorithm processes user input, standardizing symptom descriptions using regular expressions for pattern matching. This allows the system to recognize various symptom descriptions, even if the user does not use precise medical terminology. Speech synthesis further enhances user experience by reading diagnoses and recommendations aloud.

The proposed Hybrid U-Net & Improved MobileNet-V3 model was evaluated against state-of-the-art methods for multiclass skin lesion classification on the HAM10000 and Dermnet datasets. On the HAM10000 dataset, the model achieved 94.9% accuracy, 94.6% precision, 94.7% recall, an F1 score of 0.933, and an AUC of 0.957. These results demonstrate superior predictive capability compared to previous works, which often suffered from overfitting, high computational complexity, or limited generalization ability. For example, while some methods achieved high recall or AUC, they often lacked precision or overall accuracy. The proposed model balances performance across all metrics, which is crucial for reliable skin lesion classification.

On the Dermnet dataset, the model achieved 90.5% accuracy, 90.3% recall, 90% precision, an F1 score of 0.893, and an AUC of 0.935. Again, the model outperformed existing methods, demonstrating its robustness across different datasets. While some methods showed reasonable performance on Dermnet, they often lacked comprehensive evaluation metrics or suffered from lower accuracy and recall compared to the proposed model. The consistent performance across both datasets confirms the Hybrid U-Net & Improved MobileNet-V3 model's potential as a reliable tool for dermatological diagnosis in clinical practice, offering high predictive accuracy with a relatively low computational footprint.

Table 1 presents the performance analysis of the Hybrid U-Net & Improved MobileNet-V3 model on the HAM10000 dataset. From Table 1, it is evident that the concatenation of image, spectrogram, and cepstral features yields the best performance when compared to all other feature combinations. The second-best performance is achieved with the concatenation of spectrogram and cepstral features, while the concatenation of image and cepstral features achieves the third-best performance. Notably, using only spatial features (image) results in the lowest performance, highlighting the importance of incorporating diverse feature representations to enhance model accuracy.

Table 1: Performance analysis Hybrid U-Net & Improved MobileNet-V3 model on the ham10000 dataset

Parameters	**Img**	**Concatenation of (img and spec)**	**Concatenation of (img and ceps)**	**Concatenation of (ceps and spec)**	**Concatenation of (img, ceps, and spec)**
Accuracy (%)	90.10 ± 0.45	92.80 ± 0.35	93.60 ± 0.30	94.20 ± 0.25	94.90 ± 0.20
Recall (%)	89.90 ± 0.50	92.60 ± 0.40	93.40 ± 0.35	94.00 ± 0.30	94.70 ± 0.15
Precision (%)	89.60 ± 0.48	92.50 ± 0.42	93.30 ± 0.37	93.90 ± 0.28	94.60 ± 0.18

Table 2 Performance analysis of the proposed network on the dermnet dataset shows the performance of the same model on the DermNet dataset. As with Table 1, the concatenation of image, spectrogram, and cepstral features delivers the best performance, followed by the concatenation of spectrogram and cepstral features, which secures the second position. The third-best performance is seen with the combination of image and cepstral features. Again, using only spatial features results in the poorest performance, reinforcing the notion that additional domain-specific features lead to better classification outcomes. The results from Tables I and II reveal a clear distinction between spatial features alone and the concatenation of image, cepstral, and spectrogram features, emphasizing that the combination of these domains significantly improves the model's diagnostic performance for skin lesions. This is crucial, as skin lesion classification requires a high degree of accuracy, where nuanced feature representations are essential for distinguishing between subtle differences in lesion types. Moreover, both tables indicate that the proposed model shows relatively low standard deviations when using the concatenation of image, spectrogram, and cepstral features, suggesting that it is more robust with these features. This robustness enhances the model's reliability in diagnosing skin lesions, making it a valuable tool for consistent medical image analysis and real-world dermatology applications.

Table 2: Performance analysis of the proposed network on the dermnet dataset

Parameters	**Img**	**Concatenation of (img and spec)**	**Concatenation of (img and ceps)**	**Concatenation Of (ceps and spec)**	**Concatenation of (img, ceps, and spec)**
Accuracy(%)	86.20 ± 0.55	88.60 ± 0.45	89.40 ± 0.40	89.90 ± 0.30	90.50 ± 0.25
Recall (%)	86.00 ± 0.53	88.50 ± 0.47	89.20 ± 0.42	89.70 ± 0.33	90.30 ± 0.23
Precision(%)	85.70 ± 0.50	88.40 ± 0.44	89.10 ± 0.38	89.50 ± 0.30	90.00 ± 0.22

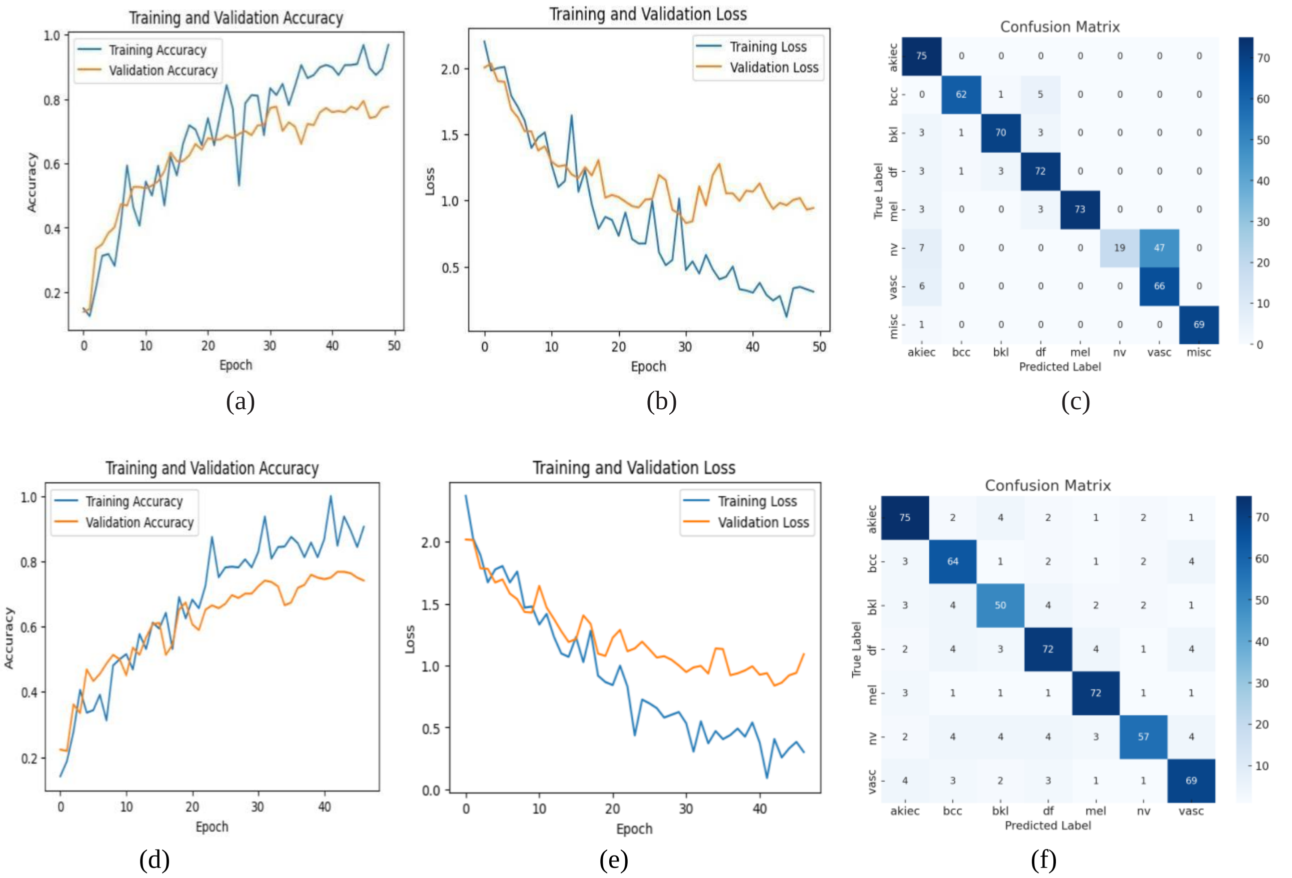

Figure 2: Performance analysis of proposed network in terms of accuracy, loss and Confusion Matrix on the test dataset for both datasets. (a) – (c) HAM10000 dataset. (d) – (f) Dermnet dataset.

Figure 2 provides a meticulous and in-depth evaluation of the proposed network's performance across two distinct datasets, namely HAM10000 and Dermnet, with a particular emphasis on key metrics such as accuracy, loss, and confusion matrices. Fig.2 (a) through Fig.2(c) are dedicated to the HAM10000 dataset, offering a granular perspective on model behaviour over the course of training. Fig.2 (a) meticulously delineates the progression of training and validation accuracy over multiple epochs, revealing a discernible upward trajectory in both metrics. The training accuracy persistently surpasses the validation accuracy, indicating a robust optimization process, although the divergence between the two suggests potential generalization limitations. Fig.2 (b) illustrates the evolution of training and validation loss, exhibiting a consistent downward trend, which signifies the model's capacity to effectively learn patterns and optimize its parameters over time. This sustained decline in loss reinforces the notion of convergence and suggests the successful minimization of discrepancies between predicted and actual outcomes.

Fig.2(c) provides an in-depth examination of the confusion matrix for the HAM10000 dataset, where the off-diagonal elements represent samples that were incorrectly classified, while the diagonal elements indicate instances that were correctly classified. The distribution of misclassifications offers valuable insights into class-wise performance, shedding light on potential areas where the model exhibits higher uncertainty or systematic bias. Transitioning to the Dermnet dataset, Fig.2 (d) through Fig.2 (f) offers a parallel examination of model performance. Fig.2 (d) mirrors the structure of Fig.2 (a), presenting a comprehensive visualization of training and validation accuracy trends. The consistently increasing accuracy across epochs underscores the model's capacity for progressive refinement. Likewise, Fig.2(e) follows the precedent set by Fig.2(b), showcasing a systematic reduction in training and validation loss, indicative of enhanced model stability and improved predictive reliability over time. Finally, Fig.2 (f) presents the confusion matrix for the Dermnet dataset, facilitating an assessment of the model's discriminatory power across multiple classes. The alignment between predicted and actual labels, as well as the distribution of misclassifications, allows for a nuanced interpretation of the model's strengths and potential weaknesses.

Collectively, this comprehensive multi-dimensional analysis elucidates the intricate learning dynamics and classification efficacy of the proposed network across both datasets. By meticulously delineating accuracy trends, loss trajectories, and class-wise predictive performance, Fig. 2 effectively encapsulates the model's proficiency in handling complex dermatological image classification tasks.

The table 3 presented encapsulates a comparative analysis of three distinct methodologies—EfficientNets, a one-dimensional multi-headed convolutional neural network (1D Multi-headed CNN), and the proposed method—evaluated on two widely recognized dermatological image datasets, HAM10000 and DERMNET. The performance of these models is meticulously assessed based on two fundamental classification metrics: accuracy and precision, both expressed as percentages. Upon scrutiny of the results, it is evident that the proposed method consistently surpasses the alternative approaches across both datasets. Notably, on the HAM10000 dataset, the proposed model achieves an impressive accuracy of 94.9%, markedly exceeding the accuracy of EfficientNets (88.1%) and the 1D Multi-headed CNN (88.57%). Similarly, in terms of precision, the proposed method attains 94.6%, significantly outperforming its counterparts, which register 88.2% and 91.12%, respectively.

A similar trend emerges when examining the DERMNET dataset, albeit with comparatively lower overall performance scores. The proposed approach again demonstrates its superiority, achieving an accuracy of 90.5% and a precision of 90%, thereby outperforming both EfficientNets (accuracy: 89%, precision: 88.95%) and the 1D Multi-headed CNN (accuracy: 88.57%, precision: 88.8%). These results underscore the efficacy of the proposed model in dermatological image classification, highlighting its potential for enhanced diagnostic accuracy in real-world clinical applications.

Table 3: Performance analysis of the proposed and the existing network

Dataset	**EfficientNets**		**1D Multi-headed CNN**		**Proposed Method**	
	Accuracy (%)	Precision (%)	Accuracy (%)	Precision (%)	Accuracy (%)	Precision (%)
HAM10000	88.1	88.2	88.57	91.12	94.9	94.6
DERMNET	89	88.95	88.57	88.8	90.5	90

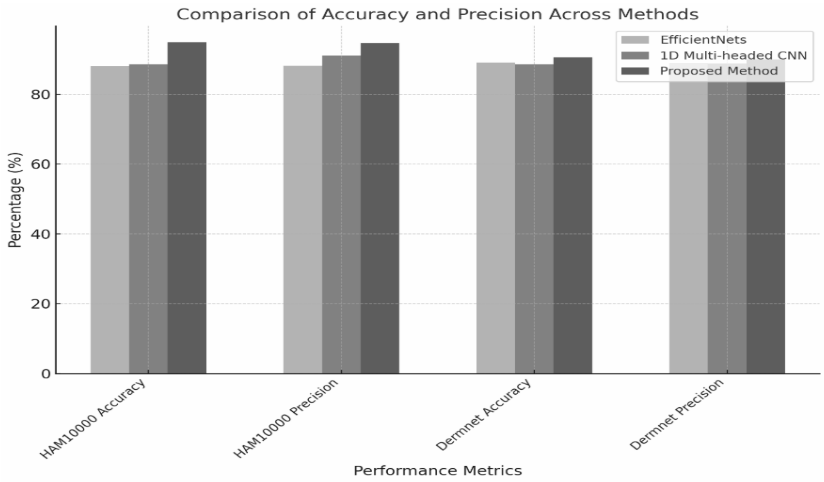

Figure 3. Comparison of accuracy and precision across methods

The figure 3 provides a comparative analysis of the performance of various methodologies, including EfficientNet, 1D Multi-Headed CNN, and the proposed Hybrid U-Net & Improved MobileNet-V3, across two prominent dermatological datasets: HAM10000 and Dermnet. The evaluation is conducted based on two critical metrics—accuracy and precision—both of which serve as pivotal indicators of a model's predictive efficacy.

For the HAM10000 dataset, the proposed method exhibits a remarkable accuracy of 94.9% and a precision of 94.6%, significantly surpassing the performance of EfficientNet and 1D Multi-Headed CNN. While 1D Multi-Headed CNN attains an accuracy of 88.57% and a precision of 91.12%, EfficientNet marginally lags behind with an accuracy of 88.1% and a precision of 88.2%. The superior performance of the proposed model underscores its robustness in effectively discerning intricate dermatological patterns within images.

A similar trend is observed in the Dermnet dataset, where the proposed method continues to outperform the existing techniques. It achieves an accuracy of 90.5% and a precision of 90%, reinforcing its adaptability across different datasets. EfficientNet, in this scenario, attains a slightly improved accuracy of 89.0% and a precision of 88.95%, demonstrating moderate consistency across datasets. However, the 1D Multi-Headed CNN records a slightly lower accuracy of 88.57% and a precision of 88.8%, indicating marginal variability in its predictive capabilities.

The pronounced disparity between the proposed method and conventional approaches highlights the efficacy of the Hybrid U-Net & Improved MobileNet-V3 architecture in capturing both spatial and textural features with heightened accuracy. The results substantiate the model's capability to generalize effectively across diverse dermatological datasets.

5. Conclusion

This study demonstrates the transformative potential of an AI-powered, two-tier healthcare chatbot system integrating deep learning for image-based skin disease classification with machine learning for symptom-driven disease prediction. The system effectively combines a Hybrid U-Net & Improved MobileNet-V3 model for accurate dermatological image analysis with a Decision Tree Classifier for predicting diseases based on user-reported symptoms. Rigorous testing on a curated skin disease image dataset and cross-validation of symptom-based models confirm the system's reliability and accuracy, achieving 94.9% and 95% respectively. This dual-layered architecture enables comprehensive consultations, including disease prediction, severity assessment, and personalized preventive recommendations.

The chatbot's versatility extends across various healthcare contexts, including skin conditions, endocrine disorders, and cardiovascular diseases, highlighting its adaptability to diverse medical challenges. By seamlessly integrating image recognition and symptom analysis, this system represents a significant advancement in telemedicine, offering an intelligent, accessible, and efficient solution for improved patient care, reduced burden on healthcare providers, and enhanced early disease detection. This innovative approach paves the way for future advancements in AI-driven healthcare solutions.

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