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Early skin disease diagnosis by using artificial neural network for internet of healthcare things

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ABSTRACT

Internet of healthcare things (IoHT) represents a burgeoning field that leverages pervasive technologies to create technology driven environments for healthcare professionals, thereby enhancing the delivery of efficient healthcare services. In remote and isolated areas, such as rural communities and boarding schools, access to healthcare professionals (especially dermatologists) can be particularly challenging. However, these areas often lack the specialized expertise required for effective skin disease consultations. Thus, the purpose of this research is to design a scheme of early skin disease diagnosis for internet of healthcare things that is accessible anywhere and anytime. In this research, the image of skin disease from patient will be taken by using a mobile phone for predicting and identifying the disease. This proposed scheme will diagnose skin disease and convert it be meaningful information. As a result, it show our proposed scheme can be the most consistent in term of accuracy and loss compared to others method. Overall, this research represents a significant step toward improving healthcare accessibility and empowering individuals to manage their own health. Furthermore, the proposed scheme is anticipated to contribute significantly to the IoHT field, benefiting both academia and societal health outcomes.

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1. INTRODUCTION

The Internet of healthcare things (IoHT) is one of the emerging technologies that is being widely accepted globally [1]–[9]. With the immense power and capability of IoHT, healthcare professionals and patients can connect to any network or service at any time and from any location [10]–[17]. They can interact with smart devices and smart objects by integrating the existing internet infrastructure for optimal resource utilization. Essentially, healthcare data can be obtained from patients through a sensory subsystem, which is then processed by a processing subsystem. The output finally will be stored in a data center. Subsequently, healthcare professionals can access this data or information anywhere and at any time. In healthcare, particularly in cases involving skin diseases, the skincare process becomes complicated due to the requirement for ongoing treatment and monitoring. This complexity arises because human skin is constantly exposed to numerous environmental and internal factors, including viruses, excessive sun exposure, diabetes, fungi or parasites, bacteria trapped in pores, environmental triggers, and genetic predispositions [18]–[26]. Skin diseases affect individuals across all age groups and can result from a combination of these factors or poor lifestyle choices and underlying medical conditions. These diseases range from chronic and incurable conditions, such as eczema and psoriasis, to malignant diseases like melanoma. While these diseases can be challenging to detect and diagnose accurately, early detection significantly improves treatment outcomes, as highlighted by recent research [27], [28]. A comprehensive review of the literature reveals a critical need for advanced skin disease detection methods. Traditional methods such as naive bayes, convolutional neural networks (CNN), and support vector machines (SVM) have been employed in previous studies to assist individuals in understanding and identifying their skin conditions [29]–[31]. These research efforts have significantly contributed to the development of our application, providing a foundational direction and framework. Despite the advancements made by previous schemes [32]–[34], their primary focus has been on disease detection rather than offering comprehensive diagnostic consultations, which are crucial for implementing IoHT systems in the remote and isolated scenario.

In this paper, we aim to design a novel scheme for early skin disease diagnosis within the IoHT framework. This scheme consists of two major steps: the detection and recognition of skin diseases, specifically eczema, pimples, and chickenpox. It detects particular shapes that distinguish the affected area from the surrounding skin. Additionally, users can capture and upload images of their affected skin areas, and the scheme will classify the skin disease, categorizing its severity into mild, moderate, or severe stages. This allows for nuanced diagnostic results, such as mild chickenpox, moderate eczema, or severe pimples. Furthermore, the system provides tailored medication suggestions and estimates the associated costs, offering a holistic approach to skin disease management. This paper is structured as follows: Section 3 presents the results and discussion of the proposed method, while Section 4 concludes with recommendations for future research and potential improvements to the system.

2. EARLY SKIN DISEASE DIAGNOSIS

In this section, we delineate our proposed early skin disease diagnosis scheme that can be applied or implemented on the IoHT platform. This scheme comprises three primary steps: skin disease detection, skin disease severity assessment, and expert consultation. Generally, the scheme operates by receiving an image of the user's skin condition, which is then processed through the skin disease detection step. The output is subsequently processed by the skin disease severity assessment to examine the seriousness of the disease. The results are cross-referenced with the data module to provide a diagnosis of skin conditions such as chickenpox, eczema, or pimples. Finally, the scheme processes the outcome to suggest medication options along with their prices.

2.1. Skin disease detection and severity measure using artificial neural network

Firstly, this subsection focuses on the implementation of artificial intelligence (AI) for image classification aimed at detecting and measure the skin diseases. Basically, this two (2) earlier steps using artificial neural network (ANN) in order to classify the skin disease image. For skin disease detection, our scheme need to classify into three (3) disease only, whether eczema, acne or chicken pox. After that, the classification will goes into severity of the disease, whether mild, moderate or severe (see Figure 1). After all, this module utilizes ANN algorithms (refer to Figure 2 for the ANN architecture) implemented in TensorFlow to achieve effective comparison of results. The algorithms were developed and executed using Python within Google Colab. To identify the most effective algorithm, all models undergo training and testing on a standardized dataset. The ANN algorithm is structured with layers [35]; the input layer receives initial data, hidden layers process this data through weighted connections and activation functions such as ReLU or sigmoid, and the output layer generates final predictions. The first layer involves M linear combinations of the d-dimensional inputs as (1). As before $x_0 = 1$, with the weights leading out from it corresponding to the biases. The quantities b_j are called activations, and the parameters $w_{ji}^{(1)}$ are the weights. The superscript '(1)' indicates that this is the first layer of the network. Each of the activations is then transformed by a nonlinear activation function g, typically a sigmoid as in (2).

$$b_j = \sum_{i=0}^{D} w_{ji}^{(1)} x_i, \qquad j = 1,2,3 \ldots\ldots M \tag{1}$$

$$z_j = h(b_j) = \frac{1}{1+\exp(-b_j)} \tag{2}$$

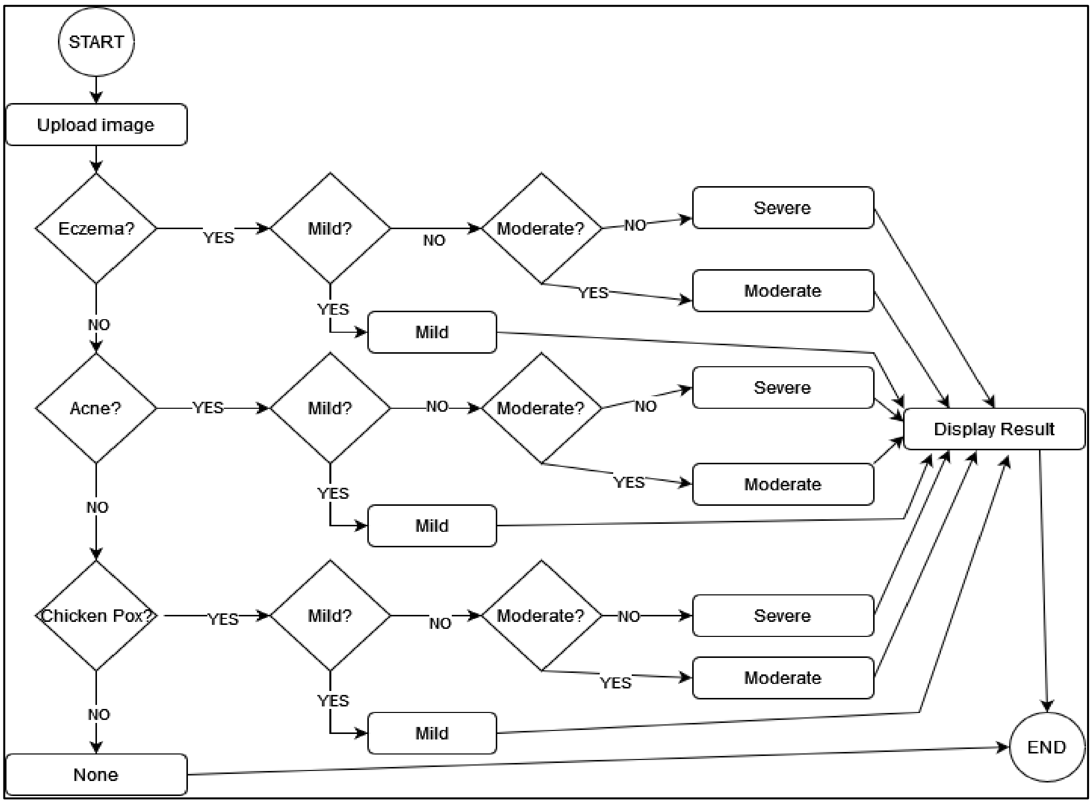

Figure 1. Skin disease detection and severity measure

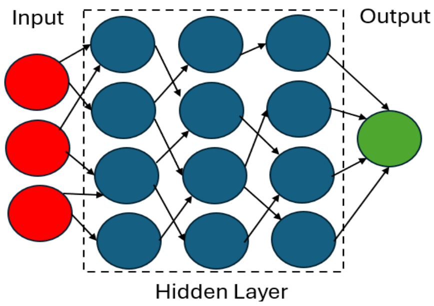

Figure 2. ANN architecture [36], [37]

During the training phase, TensorFlow adjusts weights using backpropagation, a process where errors propagate backward through the neural network. Optimization algorithms, such as gradient descent, iteratively minimize prediction errors represented by the loss function. TensorFlow streamlines this process with high-level APIs like Keras, which facilitate efficient model definition, compilation, training, and evaluation. This framework harnesses TensorFlow's computational capabilities to construct sophisticated neural networks capable of performing a wide range of tasks, from image recognition to predictive analytics.

2.2. Expert consultation

In this subsection, we focus on the implementation of the expert consultation step. Essentially, this module suggests suitable medication to the user, with the price calculated based on the recommended medication, depending on the detected disease (refer to Figure 3). As shown in that figure, the implementation is quite straightforward; however, the challenge in designing this module lies in obtaining knowledge from pharmacies and medical doctors. For instance, if the detected disease is mild eczema, the recommended medication is Eucerin Eczema relief cream. This approach also applies to other detected diseases.

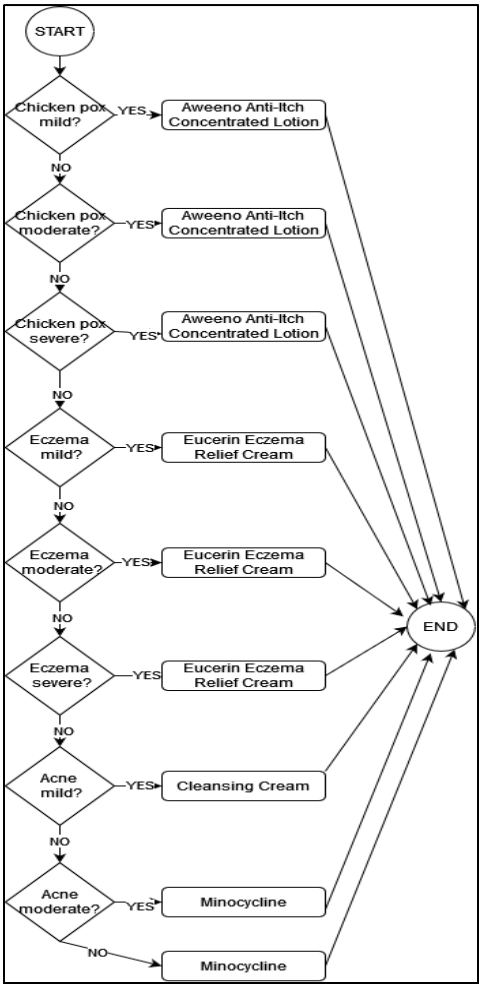

Figure 3. Expert consultation

3. RESULTS AND DISCUSSION

This section provides an evaluation of performance and discusses the results obtained. The discussion begins with an overview of data acquisition, which is crucial as it facilitates the acquisition of skin disease images. Subsequently, these images are analyzed using our proposed algorithm, Artificial Neural ANN, and compared with other algorithms such as SVM and CNN. The discussion is organized into three subsections: dataset acquisition, training performance, and accuracy assessment.

3.1. Dataset acquisition

The initial phase of dataset acquisition encompasses several crucial steps aimed at effectively preparing and utilizing image datasets for machine learning models. Data collection begins by sourcing images from repositories such as Kaggle, ensuring thorough labeling of the acquired 3547 images (see [38]–[41], for example of the dataset sample). These images encompass three primary skin diseases: chickenpox, eczema, and acne (pimple). Following data acquisition, the process proceeds to data cleaning, which involves the removal of corrupted images and normalization of image data to ensure consistency. Additionally, images are categorized into three subcategories based on the severity of the skin condition: mild, moderate, and severe, each annotated with corresponding labels. Throughout this phase, data augmentation techniques such as rotation, flipping, and color adjustments are implemented to enhance dataset diversity and mitigate overfitting. Subsequently, the dataset is partitioned into training and testing sets, as outlined in [38] for reference. In our model architecture, we employ a structured approach to build an effective neural network for classification tasks. The network begins with a convolutional layer designed to extract features from input images, utilizing 32 filters with a kernel size of 3×33 times 33×3 and ReLU activation, which is well-suited for detecting complex patterns within image data. This is followed by a MaxPooling2D layer with a pool size of 2×22 \times 22×2, which reduces the spatial dimensions of the feature maps, thereby enhancing computational efficiency and reducing the risk of overfitting. The flattened output of the convolutional and pooling layers is then passed through a series of densely connected layers. These layers include 1024, 512, and 128 units, each employing ReLU activation functions and L2 regularization with a penalty term of 0.0001. This configuration ensures that the model learns robust features while mitigating overfitting through regularization. A dropout layer with a rate of 0.1 is incorporated to further prevent overfitting by randomly dropping 10% of the neurons during training. The final layer of the network is a dense layer with units equal to the number of classes in the dataset, activated by the SoftMax function. This setup enables the model to output a probability distribution across all classes, facilitating effective classification. The model is compiled using the Adam optimizer with a learning rate of 0.00002, which is known for its efficiency in converging to optimal solutions. The categorical crossentropy loss function is used to quantify the error in classification, while accuracy serves as the primary metric for evaluating model performance. This carefully designed architecture and optimization strategy collectively contribute to the model's ability to perform robustly in diverse classification scenarios.

3.2. Training performance

Previously, the focus was on dataset acquisition, covering methods for data collection, sorting, and preparation for training. This section shifts to evaluating the training and validation accuracy of each classifier: our proposed algorithm ANN, CNN, and SVM. The discussion is structured into three (3) parts. Firstly, Figure 4 illustrates the performance of the ANN algorithm across 100 training epochs. The upper graph displays training and validation accuracy, where the blue line denotes training accuracy and the orange line represents validation accuracy. Training accuracy starts at a lower level and exhibits a sharp increase, stabilizing around 0.9. In contrast, validation accuracy starts higher and maintains relative stability, showing minor fluctuations but generally aligning closely with training accuracy after the initial epochs. The lower graph presents training and validation loss, with the blue line indicating training loss and the orange line showing validation loss. Both loss metrics experience rapid decline in the initial epochs, indicating effective learning. Training loss continues to decrease and levels off at a lower value compared to validation loss, which stabilizes at a slightly higher level. This pattern suggests effective model learning, though the slight divergence between training and validation losses may indicate minor overfitting or dataset variance.

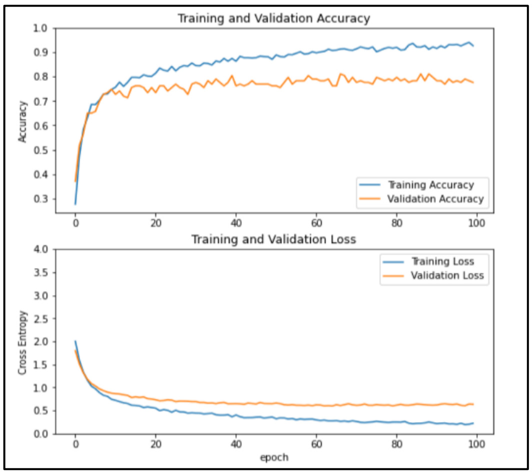

Figure 4. Graph of training and validation accuracy with loss using the ANN algorithm

Secondly, Figure 5 illustrates the training progression of a CNN model across 100 training steps. The left graph depicts "training and validation accuracy," while the right graph shows "training and validation loss." Both graphs reveal a pronounced overfitting pattern: the training accuracy (blue line) swiftly rises to approximately 95% and stabilizes, whereas the validation accuracy (orange line) fluctuates around 40%-50%. Similarly, the training loss (blue line) rapidly decreases and remains minimal, whereas the validation loss (orange line) exhibits an upward trend with notable volatility, occasionally peaking above 3.5. This significant disparity between training and validation metrics indicates that the model is memorizing specific details of the training data rather than learning generalizable features. While the model performs well on the training set, it struggles to generalize to unseen data in the validation set. Addressing this overfitting scenario may require adjustments to the model architecture, incorporation of regularization techniques, or adoption of data augmentation strategies to enhance the model's ability to generalize effectively. Thirdly, Figure 6 presents the performance of an SVM algorithm during training. The left graph illustrates the training and validation accuracy over 100 training steps. Both accuracies start at lower levels and exhibit fluctuations, with the training accuracy consistently maintaining a slightly higher level than the validation accuracy, stabilizing near 0.9 towards the conclusion of training. This suggests that the model achieves a satisfactory fit to the training data without significant overfitting, as indicated by the close alignment of validation accuracy. In the right graph, training and validation loss across the same training steps are depicted. The training loss decreases sharply and stabilizes at a low value, signifying effective learning. In contrast, the validation loss initially decreases but displays variability, indicating some response to model adjustments with less consistency compared to the training loss. This variability suggests areas where improvements in model generalization could be explored, although the overall low level of loss is promising. Together, these graphs provide a comprehensive overview of the model's learning dynamics, highlighting its strengths and areas for potential refinement through further tuning strategies.

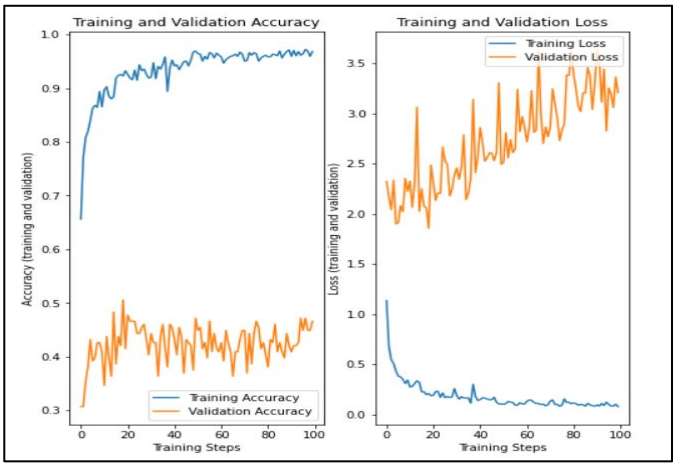

Figure 5. Graph of training and validation accuracy using the CNN algorithm

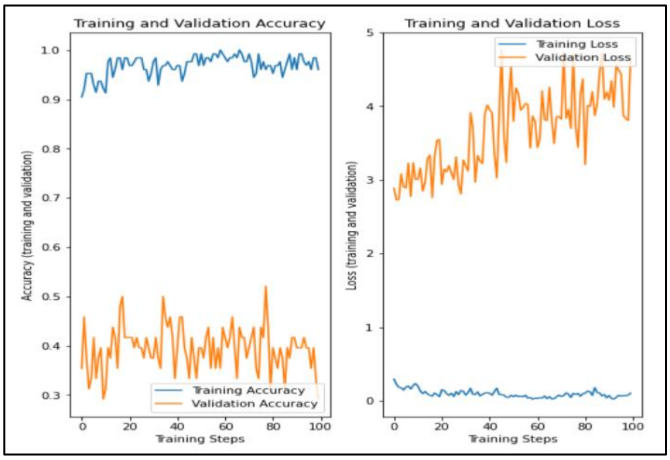

Figure 6. Graph of training and validation accuracy using the SVM algorithm

3.3. Performance accuracy

In terms of performance assessment, Figure 7 demonstrates that our proposed method (MDES using ANN) consistently surpasses both SVM and CNN in detecting the severity of chickenpox, pimples, and eczema. Specifically, for chickenpox, the proposed method achieves high accuracy across all severity levels, particularly excelling in mild and severe cases. In the case of pimples, it exhibits exceptional performance in detecting severe cases, while demonstrating moderate accuracy for mild and moderate cases. Regarding eczema, the proposed method shows robust performance, especially in moderate and severe cases. In contrast, SVM generally underperforms, especially noticeable in moderate cases of eczema, while CNN shows competitive performance in detecting mild and moderate cases of pimples but lags behind in other aspects compared to the proposed method. Overall, the proposed method proves to be the most effective across different types of skin diseases and severity levels. Furthermore, Figure 8 presents a bar chart depicting the accuracy of three classifiers: SVM, the proposed method (MDES using ANN), and CNN, in diagnosing three skin diseases: eczema, chickenpox, and pimples. The proposed method (MDES using ANN) significantly outperforms the other classifiers with an accuracy of 77%, underscoring its superior effectiveness. In contrast, the SVM classifier achieves the lowest accuracy at 40%, indicating its limited efficacy for this diagnostic task. The CNN classifier performs better than SVM but still falls short of the proposed method, achieving an accuracy of 48%. Overall, the proposed method emerges as the most reliable option for diagnosing these skin diseases, highlighting its potential to enhance diagnostic accuracy.

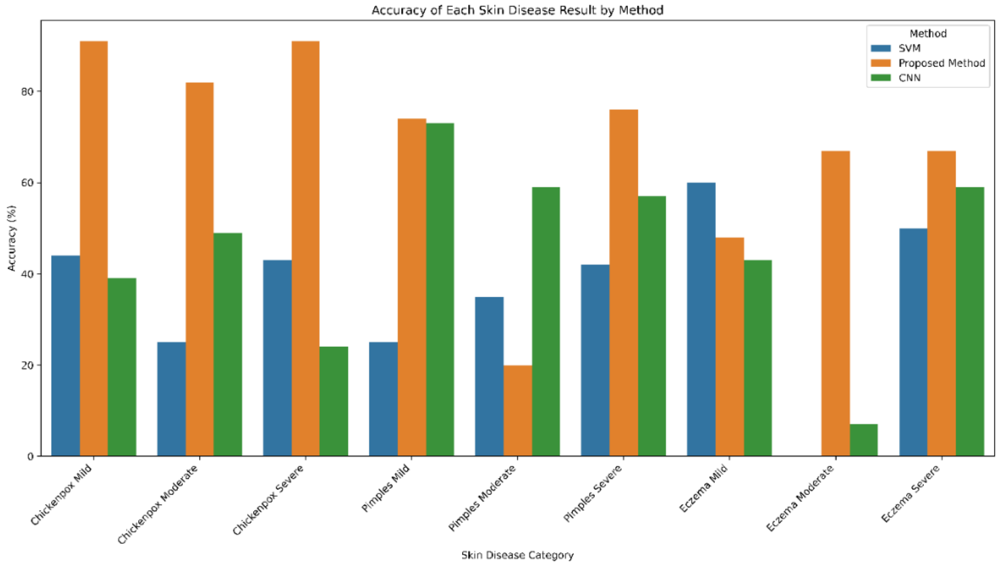

Figure 7. Comparison algorithm of SVM, CNN with proposed method with on skin disease diagnosis

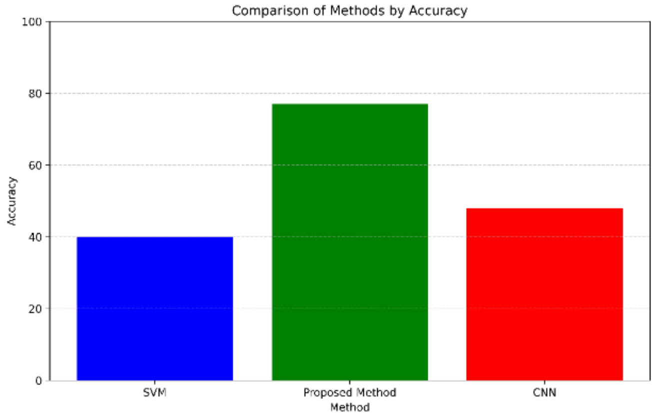

Figure 8. Performance accuracy of SVM, CNN with proposed scheme

4. CONCLUSION

The IoHT represents a rapidly evolving field that utilizes pervasive technologies to create technology-driven environments for healthcare professionals, thereby enhancing the delivery of efficient and effective healthcare services. This is particularly significant in remote and isolated areas, such as rural communities and boarding schools, where access to healthcare professionals (especially dermatologists) is often limited. These regions frequently lack the specialized expertise necessary for accurate skin disease consultations. In response to this challenge, this research has introduced a novel scheme for early skin disease diagnosis within the IoHT framework, designed to be accessible anytime and anywhere. To achieve this, images of skin conditions are captured using a mobile phone, enabling the prediction and identification of diseases. Our proposed scheme then processes these images to diagnose skin conditions, converting the data into meaningful clinical information. Notably, our findings demonstrate that the application of ANN to a comprehensive dataset of 3,547 skin disease images resulted in a significant diagnostic accuracy of 77%. This performance surpasses that of conventional algorithms such as CNN and SVM, underscoring the efficacy of ANN in handling extensive datasets for precise diagnostic purposes. The significance of this research is underscored by its potential to democratize access to dermatological expertise, particularly in areas where direct access to specialized healthcare professionals is constrained. By enabling users to identify skin conditions through a user-friendly interface and offering tailored medical advice and cost estimates, our system addresses critical gaps in healthcare delivery. Furthermore, by educating communities on effective skin health practices, the system contributes to preventive healthcare initiatives. Looking ahead, potential enhancements to the system include refining its diagnostic capabilities through the continuous expansion of the dataset and the integration of more advanced machine learning techniques. Ongoing monitoring and iterative improvements of the system's performance will be essential to ensure its sustained effectiveness and applicability across diverse healthcare settings. In conclusion, the development of this early skin disease diagnosis scheme represents a significant advancement in improving healthcare accessibility and empowering individuals to effectively manage and prevent skin diseases. Additionally, this scheme is poised to make meaningful contributions to the field of IoHT, benefiting both academic research and public health outcomes.

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