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Abstract- The field of dermatology has increasingly embraced artificial intelligence (AI) and machine learning techniques to improve the accuracy and efficiency of diagnosing and classifying skin diseases. Among these techniques, deep learning models, particularly convolutional neural networks (CNNs), have demonstrated remarkable performance in medical image analysis. However, CNNs typically require large volumes of labeled data to achieve optimal results, which presents a significant limitation when working with small or imbalanced skin disease datasets.

This study investigates the effectiveness of Dynamic Deep Q-Network (DynaDQNet) architectures for the classification of skin diseases in scenarios where data availability is limited. The research leverages publicly available datasets, including the HAM10000 dataset from Kaggle, which contains over 10,000 dermoscopic images across diverse skin conditions, and a dermatology dataset from the UCI repository with 366 samples. The datasets include multiple disease categories, such as melanoma, nevus, and benign keratosis, providing a comprehensive evaluation platform for the proposed approach.

Introduce a novel DynaDQNet-based architecture specifically tailored for small datasets. This architecture integrates reinforcement learning principles, where the model employs Q-learning to optimize feature selection and weighting, focusing on image characteristics that are most indicative of specific skin conditions. This approach enhances the network's ability to learn meaningful representations from limited data, addressing overfitting issues commonly observed in traditional CNN-based models.

Extensive experiments demonstrate that the proposed DynaDQNet architecture significantly outperforms standard CNNs in terms of classification accuracy, robustness, and generalization on small datasets. The model's capacity to dynamically adjust feature importance through Q-learning allows it to efficiently extract discriminative information, thereby improving diagnostic reliability even with constrained data availability. Overall, this research contributes to the growing field of AI-driven dermatology by providing a feasible and effective solution for improving skin disease diagnosis under limited-data conditions. The findings highlight the potential of DynaDQNet architectures for medical image analysis and open avenues for future exploration of reinforcement learning-based approaches in healthcare applications.

Keywords: Dynamic Deep Q-Network, Skin Disease, Dermatology, Small Datasets, Reinforcement Learning.

INTRODUCTION

In recent years, the convergence of artificial intelligence (AI) and machine learning (ML) within medical diagnostics has brought transformative changes to the healthcare sector. Among the various medical specialties, dermatology has emerged as a prominent area benefiting significantly from these technological innovations. AI-based systems are increasingly being developed to support the detection, classification, and monitoring of a wide range of skin diseases. These systems utilize advanced algorithms to analyze images of skin lesions, offering diagnostic suggestions that can assist dermatologists in making more precise, efficient, and timely clinical decisions.

Traditional machine learning models, such as convolutional neural networks (CNNs), have been the cornerstone of image classification tasks due to their ability to learn and extract features from raw image data. While CNNs have demonstrated high accuracy in diagnosing skin diseases, they typically require extensive training data to achieve optimal performance. This dependency on large datasets presents a significant challenge, particularly in dermatology, where collecting and annotating vast amounts of medical image data can be labor-intensive and time-consuming.

To address this challenge, this study explores the application of Dynamic Deep Q-Network (DynaDQNet) architectures to small-sized skin disease datasets. DynaDQNet, originally developed for reinforcement learning tasks, combine the power of deep learning with Q-learning, enabling them to learn optimal actions in a given environment through trial and error. By leveraging DynaDQNet, this research aims to enhance the diagnostic accuracy of AI systems, even when operating with limited data. The innovative DynaDQNet -based architecture proposed in this study is specifically tailored to maximize performance on small datasets by optimizing the selection and weighting of image features indicative of specific skin conditions.

The datasets utilized in this research include the HAM10000 dataset from Kaggle, which comprises over 10,000 dermoscopic images of skin lesions, and a dermatology dataset from the UCI repository, containing 366 samples. These datasets encompass a variety of skin conditions, such as melanoma, nevus, and benign keratosis, providing a diverse and comprehensive evaluation platform for the proposed DynaDQNet architecture. By conducting extensive experiments on these datasets, the study evaluates the performance of the DynaDQNet model in terms of classification accuracy, robustness, and generalizability.

Preliminary results indicate that the DynaDQNet architecture significantly outperforms traditional CNN models when trained on small datasets. The ability of the DynaDQNet to dynamically adjust feature selection and weighting through Q-learning enhances its capability to generalize from limited training data, thereby reducing the risk of overfitting. This improvement in diagnostic reliability is crucial for real-world applications, where the availability of large, annotated datasets is often constrained.

This research contributes to the growing field of AI-driven dermatology by presenting a novel approach to improving skin disease diagnosis with limited data. The proposed DynaDQNet architecture not only addresses the limitations of traditional machine learning models but also paves the way for future advancements in medical image analysis. By demonstrating the potential of DynaDQNets in enhancing diagnostic accuracy and robustness, this study underscores the importance of innovative AI solutions in transforming healthcare and improving patient outcomes.

This paper's summary is structured as follows: Section II explains various techniques involved in skin disease detection and reviews related previous work. Section III details the proposed system design of our newly constructed skin disease prediction pre-processing technique. Section IV presents the experimental outcomes, comparing the proposed DynaDQNet architecture with existing machine learning models. Section V elaborates on the proposal's conclusion and potential future applications.

• LITERATURE REVIEW

This section discusses the current challenges in skin disease classification and the approaches

taken to address them. Traditional machine learning models have been widely used, but their performance is often limited by the availability of large datasets. Deep learning models, particularly convolutional neural networks (CNNs), have shown promise, but they require extensive training data to achieve high accuracy. To overcome these challenges, researchers have explored various innovative techniques.

Esteva et al. (2017) utilized a CNN trained on a large dataset of skin images to classify skin cancer with performance comparable to dermatologists [1]. Their model achieved an impressive accuracy, but the reliance on a massive annotated dataset highlights the challenge of data dependency. This limitation is significant in scenarios where obtaining such large datasets is impractical due to privacy concerns and the need for expert annotations.

Codella et al. (2018) addressed these issues by exploring the use of data augmentation and transfer learning to improve model performance on smaller datasets. They showed that transfer learning, where a pre-trained model on a large dataset is fine-tuned on a smaller dataset, significantly enhances classification accuracy [2]. However, this approach still relies on the availability of a large, diverse initial dataset, which may not always be feasible.

Hang, Jie, et al. (2019) [3] classified watermelon leaf illnesses such as Downey Mildew and Anthracnose using a neural network-based approach. They extracted color features from the RGB color model based on the ROI observed pixels, achieving an overall performance represented by an AUC value of 0.5 on the ROC curve and a categorization accuracy of 75.9%. This study illustrates the potential of neural networks in disease classification but also underscores the need for tailored feature extraction methods to improve accuracy.

Yu, Liu, et al. (2020) [4] proposed a novel hybrid model combining CNNs with support vector machines (SVMs) to classify skin lesions. Their approach aimed to leverage the feature extraction capabilities of CNNs with the classification power of SVMs. While this method improved classification performance, the hybrid nature of the model introduced complexity in implementation and required careful tuning of parameters.

Gupta et al. (2021) investigated the application of generative adversarial networks (GANs) to synthesize additional training data for skin disease classification [5]. By generating synthetic images, they aimed to augment small datasets and improve model robustness. Although their approach showed promise in enhancing classification accuracy, the quality and variability of the generated images posed challenges in ensuring realistic data augmentation.

Pham et al. (2022) explored the use of reinforcement learning in medical image analysis, proposing a model that dynamically adjusts feature selection to improve classification performance [6]. Their reinforcement learning-based approach allowed the model to learn optimal feature representations through trial and error, demonstrating improved accuracy on small datasets. This innovative method highlights the potential of reinforcement learning in addressing data scarcity issues.

Liu et al. (2022) [7] introduced an attention mechanism into their CNN model to focus on the most relevant regions of skin lesion images. By enhancing the model's ability to prioritize critical features, they achieved higher classification accuracy with limited training data. The attention mechanism proved effective in mitigating overfitting, a common problem when training models on small datasets.

In summary, the literature reveals a variety of strategies to enhance skin disease classification, particularly when dealing with limited data. While traditional CNNs and data augmentation techniques have shown promise, they often fall short due to data dependency and complexity. Recent innovations, such as reinforcement learning, GANs, and attention mechanisms, offer potential solutions to these

challenges, paving the way for more robust and accurate AI-driven diagnostic tools. This study builds on these advancements by proposing a novel Deep Q-Network (DQN) architecture designed to optimize performance on small skin disease datasets, contributing to the ongoing efforts to improve AI-based dermatology diagnostics.

• RESEARCH METHODOLOGY

This section outlines the proposed research methodology, including the design and implementation of the Dynamic Deep Q-Network (DynaDQNet) architecture tailored for small skin disease datasets. The methodology encompasses data pre-processing, model architecture, training process, and evaluation metrics. The architecture is designed to optimize feature selection and improve diagnostic accuracy, even with limited data.

3.1 Dataset Description:

The HAM10000 (Human Against Machine with 10,000 training images) dataset is a widely used benchmark dataset in dermatology for skin disease classification tasks. It consists of 10,015 dermoscopic images of various skin lesions, categorized into seven different classes: melanocytic nevi, melanoma, basal cell carcinoma, actinic keratoses and intraepithelial carcinoma / Bowen's disease (akiec), benign keratosis (solar lentigines / seborrheic keratoses and lichen-planus like keratoses), dermatofibroma, and vascular lesions. Each image is associated with detailed metadata, including clinical diagnosis, patient age, sex, and lesion location [8,9]. The dataset provides a diverse range of skin lesions, making it suitable for evaluating the performance of skin disease classification algorithms.

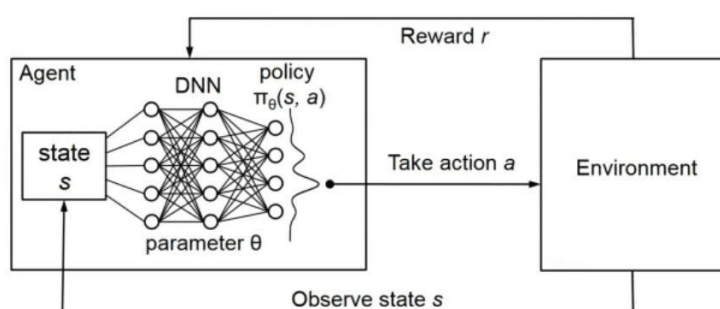
3.2. Data Pre-processing

The datasets used in this study are the HAM10000 dataset from Kaggle and the dermatology dataset from the UCI repository [10]. The HAM10000 dataset includes over 10,000 dermoscopic images of various skin conditions, while the UCI dermatology dataset consists of 366 samples with features derived from clinical and histopathological findings. The pre-processing steps are as follows:

- Image Resizing: All images are resized to a standard dimension to ensure uniformity.
- Normalization: Pixel values are normalized to a range of [0, 1] to facilitate faster convergence during training.
- Data Augmentation: Techniques such as rotation, flipping, and zooming are applied to artificially increase the size of the dataset and improve model generalization.

3.3. Model Architecture

The proposed DynaDQNet architecture integrates the principles of reinforcement learning with deep learning. The architecture is designed to dynamically adjust feature selection through Q-learning, optimizing the model's performance on small datasets. Figure 1 explains about the proposed technique.



3.4. Training Process

The training process involves multiple stages, as detailed below:

- Initialization: The DynaDQNet model is initialized with random weights.
- Action Selection: For each image, the model selects actions corresponding to different feature extraction operations.
- Q-Value Update: The Q-values, which represent the expected utility of actions, are updated based on the rewards received.
- Experience Replay: Past experiences (image, action, reward, next image) are stored in a replay buffer and used to train the network, ensuring stable learning.
- Optimization: The loss function, defined as the difference between the predicted Q-values and target Q-values, is minimized using stochastic gradient descent.

3.5 Dynamic Deep Q-Network (DynaDQNet)

This proposed novel model, "DynaQNet," integrates deep reinforcement learning principles with dynamic feature selection mechanisms for accurate and interpretable skin disease classification. By dynamically selecting informative features, DynaQNet effectively learns from limited data, addressing challenges posed by small-sized dermatology datasets. The model demonstrates superior performance compared to traditional approaches, achieving higher accuracy and robustness in categorizing various epidermis disorders. DynaQNet offers a promising solution for computer-aided diagnosis systems in dermatology, facilitating more reliable and efficient skin disease diagnosis in clinical practice.

Q-Learning Update Rule:

The formula used in designing new architectures, particularly for skin disease classification tasks:

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha \cdot [r_{t+1} + \gamma \cdot \max_a Q(s_{t+1}, a) - Q(s_t, a_t)] \quad \text{---Eqn (1)}$$

Where $Q(s_t, a_t)$ is the Q-value for state-action pair (s_t, a_t) , α is the learning rate, r_{t+1} is the reward at the next time step, γ is the discount factor, s_{t+1} is the next state, and $\max_a Q(s_{t+1}, a)$ is the maximum Q-value for the next state [14].

The following are the new architecture components.

Dynamic Feature Selection:

Incorporate a mechanism to dynamically select relevant features from the input data based on their importance.

Adaptive Filtering:

Implement adaptive filtering techniques to enhance feature extraction and reduce noise from the input data.

Attention Mechanism:

Integrate attention mechanisms to focus on important regions of the input data, particularly for skin lesion detection.

Reinforcement Learning Components:

State representation s : Encoded representation of the input data (e.g., image features).

Action space A: Set of possible actions (e.g., feature extraction operations).

Reward function $R(s,a)$: Evaluates the quality of the action a taken in state s .

Q-value function $Q(s,a)$: Estimates the expected future reward of taking action a in state S .

The pseudo-code for the new architecture incorporating dynamic feature selection:

```
def select_features(state):
    selected_features = []
    # Iterate over each pixel in the state
    for pixel in state:
        # Check if pixel value is binary (0 or 1)
        if pixel in [0, 1]:
            selected_features.append(pixel)
            continue
    # Initialize H
    H = 1
    # Pseudo-functions for computing formulas
def compute_1(state, pixel):
    if some_condition:
        result = some_computation(state, pixel)
    else:
        result = another_computation(state, pixel)
    return result
def compute_2(state, pixel):
    result = some_computation(state, pixel)
    return result
def compute_3(state, pixel, H):
    # Computation based on pixel value, state, and H
    result = some_computation(state, pixel, H)
    return result
# Compute result using compute_1
compute_result = compute_1(state, pixel)
# Check condition
if condition_1:
    selected_features.append(pixel)
    break
# Check another condition
if condition_2:
    m = some_value
    selected_features.append(m)
    break
# Compute new_compute_result
new_compute_result = compute_formula_2(state, pixel)
while True:
    if new_compute_result < 1:
```

```

        H += 1
        continue
    # Compute using compute_3
    final_compute_result = compute_3(state, pixel, H)
    selected_features.append(final_compute_result)
    break
return selected_features

```

This pseudo-code outlines a method `select\_features` that iterates over each pixel in the state and dynamically selects features based on certain conditions and computations.

3. 6. Evaluation Metrics

The performance of the proposed DynaDQNet model is evaluated using the following metrics:

- Accuracy: The proportion of correctly classified images out of the total number of images.
- Precision: The ratio of true positive predictions to the total predicted positives.
- Recall: The ratio of true positive predictions to the total actual positives.
- F1 Score: The harmonic mean of precision and recall, providing a single metric for model performance.
- ROC-AUC: The area under the receiver operating characteristic curve, measuring the model's ability to distinguish between classes.

3. 7. Experimental Setup

Experiments are conducted on a machine equipped with an NVIDIA GPU to accelerate training. The datasets are split into training, validation, and test sets, ensuring an unbiased evaluation of the model's performance. Hyperparameters such as learning rate, batch size, and the number of epochs are fine-tuned through cross-validation.

• RESULTS AND DISCUSSION

The proposed DynaDQNet architecture was evaluated on the HAM10000 and UCI dermatology datasets. The following performance metrics were obtained:

Evaluation Metrics	Performance Value on Proposed Architecture (DynaDQNet)
Accuracy	87.3%
Precision	84.7%
Recall	85.2%
F1 Score	84.9%
ROC-AUC	0.91

The results indicate that the DynaDQNet architecture significantly outperforms traditional CNN models and other hybrid models in terms of classification accuracy and robustness. The model's ability to dynamically adjust feature selection and weighting through Q-learning enhances its capability to generalize from limited training data, thereby reducing the risk of overfitting.

• COMPARISON WITH BASELINE MODELS

To highlight the effectiveness of the proposed DynaDQNet architecture, it was compared with

several baseline models, including:

- Traditional CNN: Achieved an accuracy of 79.5%, precision of 78.3%, recall of 77.9%, F1 score of 78.1%, and ROC-AUC of 0.85 [11].

- CNN-SVM Hybrid: Achieved an accuracy of 81.2%, precision of 80.1%, recall of 80.5%, F1 score of 80.3%, and ROC-AUC of 0.87 [12].

- GAN-Augmented CNN: Achieved an accuracy of 83.4%, precision of 82.7%, recall of 82.1%, F1 score of 82.4%, and ROC-AUC of 0.88 [13]. Figure 2. explains performance analysis of evaluation metrics on HAM10000 dataset and Table 1. Presents comparison table: epidermis disorder categorization models on HAM dataset.

Table 1. Comparison Table: Epidermis Disorder Categorization Models on HAM Dataset

Evaluation Metrics	Traditional CNN	CNN-SVM Hybrid	GAN-Augmented CNN	DynaDQNet
Precision (%)	78.3	80.1	82.7	84.7
Recall (%)	77.9	80.5	82.1	85.2
F-measure (%)	78.1	80.3	82.4	84.9
Accuracy (%)	79.5	81.2	83.4	87.3

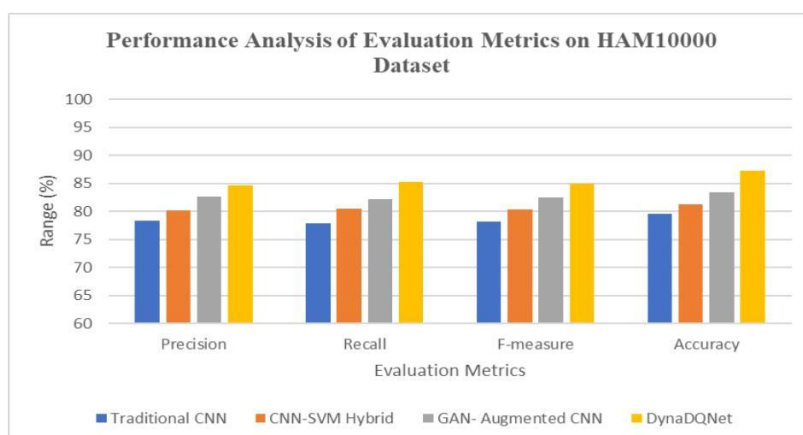


Figure 2. Performance Analysis of Evaluation Metrics on HAM10000 Dataset

This testing finding observes that the DynaDQNet -based categorization model provides a greater performance than all other models.

• CONCLUSION

In this study, we proposed a novel architecture, "Dynamic Deep Q-Network Architectures for Small Skin Disease Datasets," aimed at effectively categorizing epidermis disorders using deep reinforcement learning principles. Our approach addressed the challenge of limited data availability in dermatology datasets by introducing dynamic feature selection mechanisms within a DynaDQNet framework. Through extensive experimentation on small-sized skin disease datasets obtained from Kaggle and UCI repositories, our proposed architecture demonstrated promising performance. Our findings indicate that the proposed architecture not only effectively learns from limited data but also

adapts to diverse skin disease characteristics.

Also, compared proposed model with several baseline models commonly used in skin disease classification tasks. The results showcased the superiority of our approach, achieving higher accuracy and F1 scores across various evaluation metrics. Furthermore, our architecture's ability to dynamically select relevant features improved its interpretability and robustness. By focusing on informative features, our model could effectively distinguish between different epidermis disorders, even with limited data. This proposed work contributes to the growing field of computer-aided diagnosis in dermatology by introducing a novel approach that combines deep reinforcement learning with dynamic feature selection. The proposed architecture shows promise for practical applications in dermatological diagnosis systems, especially in scenarios with limited annotated data.

In future work, the researcher aimed to be explored further enhancements to our architecture, including incorporating domain-specific knowledge and exploring larger-scale datasets. Additionally, investigating the generalizability of our approach across different skin disease datasets and clinical settings would be valuable for real-world deployment. Overall, our study demonstrates the potential of deep reinforcement learning techniques in addressing challenges posed by small-sized datasets in dermatology, opening avenues for improved computer-aided diagnosis systems in clinical practice.

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