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Skin Diseases Detection Using Convolution Neural Network

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Abstract - As long as dermatological care encounters challenges, advancements in the accuracy of diagnosis and the efficacy of treatment are imperative. Pioneering work has shown that integrating You Look Only Once (YOLO) architecture with Convolution Neural Networks (CNNs) is a promising alternative. This study investigates the transformative potential and provides fresh perspectives on the diagnosis of skin conditions. By means of technical investigation, we uncover its ability to transform still images into proactive changes in dermatological diagnostics. Furthermore, its wide-ranging implications are explored, encompassing enhancements to diagnosis precision, optimization of treatment strategies, and ultimately, better patient results. The paper emphasizes the crucial roles that CNNs and YOLO architecture will play in defining the path by closely reviewing empirical data and real-world applications.

***Key Words*: ** Convolution Neural Networks (CNN), You Look Only Once (YOLO) architecture, Image processing, Skin diseases classification, Diagnostic accuracy.

1.INTRODUCTION

Dermatology is a branch of medicine that sits at the interface between visual assessment and medical diagnosis. Given that the skin is a reflection of internal health, prompt and correct diagnosis of dermatological diseases is essential to their appropriate management and treatment. Nevertheless, difficulties still exist in the field of dermatological care despite notable breakthroughs in medical technology, notably with regard to the precision of diagnosis and the effectiveness of treatment [1]. Recent years have seen a breakthrough in medical imaging and diagnostics due to the convergence of computer vision and artificial intelligence (AI). Convolutional Neural Networks (CNNs) are a potent tool for picture categorization and recognition tasks among the many AI techniques available. Simultaneously, the You Only Look Once (YOLO) architecture's development has transformed the diagnosis of skin illnessesin a pictures and video streams, allowing for the fastest and most accurate real-time analysis possible [2]. In this context, novel initiatives have started investigating the combination of CNNs and YOLO architecture in dermatology. This study explores the integration's revolutionary potential and opens up new avenues for the identification and treatment of skin conditions. Through an exploration of the technical details of CNNs and YOLO architecture, we want to reveal how they might be used to convert static photos into proactive shifts in dermatological diagnosis [3]. Long-standing issues in dermatological care may be resolved with the use of CNNs and YOLO architecture. Clinical practitioners' subjective visual assessments are a common component of traditional dermatological diagnosis techniques, which can lead to differences in interpretation and mistakes in diagnosis. Furthermore, it is extremely difficult to diagnose skin disorders accurately and promptly due to their enormous number and diversity [4].

CNNs provide an answer to the challenges of dermatological image analysis because of their capacity to extract hierarchical characteristics from unprocessed pixel data. CNNs can learn to identify between various skin lesions, textures, and patterns with impressive accuracy by utilizing massive datasets of annotated photos. Moreover, CNNs can adapt and generalize to different dermatological circumstances even when there is a lack of training data because to the transfer learning approach [5]. The use of CNNs in dermatological diagnosis is not without difficulties, though. To guarantee CNN models' dependability and generalizability across a range of patient groups and skin types, one of the main challenges is the necessity for thorough validation and assessment. Furthermore, as CNN-based diagnostic systems use opaque algorithms, there is ongoing discussion on their interpretability may hinder the acceptability and adoption of their recommendations by physicians by hiding the reasoning behind them. This is where CNNs' capabilities are enhanced by the integration of YOLO architecture, especially in real-time object detection and localization. YOLO processes the entire image in a single feedforward pass, in contrast to typical CNNs, which need numerous runs over an image to detect objects. This allows for the quick and effective detection of multiple items at once. This expedites dermatological diagnosis and makes it easier to incorporate AI-powered decision support systems into clinical procedures [6]. Moreover, the broad implications of CNNs and YOLO architecture go beyond diagnostic precision and include treatment strategy improvement and, in the end, improving patient outcomes. Through the examination of actual data and practical implementations, this study is to highlight how crucial CNNs and YOLO architecture will be in determining the direction of dermatological care in the future. The following sections will cover the technological underpinnings of CNNs and YOLO architecture, their applications in dermatological diagnostics, and the opportunities and challenges that come with integrating them. We want to clarify the revolutionary potential of this novel technique and its implications for the future of dermatological treatment by methodically analyzing and synthesizing the available literature and empirical data [7].

Further investigation into the You Only Look Once (YOLO) architecture and Convolutional Neural Networks (CNNs) integration in dermatological care reveals that this creative solution not only solves current issues but also adds new perspectives to the field. Our study intends to investigate the whole range of possibilities given by CNNs and YOLO architecture in dermatological care, with an emphasis on improving patient outcomes, optimizing treatment options, and advancing diagnostic accuracy. Creating innovative image analysis algorithms that take advantage of the complementing features of CNNs and YOLO architecture is a crucial component of this research. We can attain previously unheard-of levels of speed, accuracy, and efficiency by fusing the real-time object recognition skills of YOLO with the deep learning capabilities of CNNs.We can attain previously unheard-of levels of speed, precision, and efficiency in dermatological diagnostics with the help of YOLO's real-time object detection capabilities. Clinicians will be able to quickly recognize and categorize a variety of skin lesions, from common ailments like eczema and acne to uncommon illnesses and signs of systemic disorders, thanks to these sophisticated algorithms [8]. Additionally, the goal of our project is to investigate how CNNs and YOLO architecture might support interdisciplinary cooperation and knowledge sharing among dermatologists. We may use a variety of viewpoints and skill sets to promote innovation in dermatological care by involving dermatologists, data analysts, computer scientists, and other stakeholders in cooperative research projects. We can hasten the creation and validation of AI-driven diagnostic tools by utilizing shared datasets, open-access resources, and cooperative research platforms,we can expedite the creation and verification of AI-powered diagnostic instruments and decision assistance platforms.

In addition to its clinical uses, the research intends to investigate the legal, social, and ethical ramifications of using CNNs and YOLO architecture in dermatological practice. Concerns around algorithm bias, data privacy, and the proper application of AI in healthcare must be addressed as these technologies advance. We can make sure that these technologies are implemented in a way that supports patient safety, trust, and wellness by involving stakeholders in conversations about transparency, accountability, and equity in AI-driven dermatological diagnostics [9]. Furthermore, the study aims to investigate how CNNs and YOLO architecture can revolutionize dermatological training and teaching. Future dermatologists can receive better training and be equipped with the necessary abilities by creating interactive learning modules, virtual simulations, and AI-powered teaching tools,we can improve the education of aspiring dermatologists and provide them with the know-how required to use AI technologies in clinical settings. We can make sure that doctors are prepared to take advantage of these game-changing technologies by incorporating AI into dermatological residency programs and CME courses. The project is essentially an interdisciplinary attempt to investigate the revolutionary possibilities of combining CNNs with YOLO architecture in dermatological care. Our mission is to transform the detection, diagnosis, and treatment of dermatological disorders by improving patient outcomes, treatment

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strategy optimization, and diagnostic accuracy. We aim to use AI to improve patient health and wellbeing globally through cooperative research, ethical involvement, and creative educational activities [10].

2. RELATED WORKS

The authors G. Sasiakala, Bollineni AmruthaPriya, and Gangavarapu LakshmiPriya (2022) demonstrated proficiency in developing a CNN model for the detection and classification of skin diseases, achieving a commendable 70% accuracy rate using 938 images. Their model effectively classified diseases such as Melanoma, Nevus, and Seborrheic Keratosis utilizing INCEPTIONv3, ALEXNET, and RESNET architectures. They also provided valuable diagnosis and treatment suggestions, highlighting the potential for performance improvement in CNN-based disease recognition systems [11]. Suraj Verma, Mohammad Abdur Razzaque, and Usanut Sangtongdee (2021) made significant strides in digital diagnosis by developing a hybrid deep neural network system for Hand, Foot, and Mouth Disease (HFMD). Their model exhibited exceptional accuracy in identifying HFMD, contributing to accurate diagnoses and paving the way for user-friendly interfaces in medical innovation [12]. Md. Nazmul Hossen and Vijayakumar Panneerselvam (2023) introduced a skin disease model with notable precision rates for various conditions, leveraging federated learning to ensure privacy while achieving high accuracy with 2500 clients. They explored the effectiveness of VGG16 and Alex Net architectures, proposing enhancements for improved performance across different disease classes [13]. Kritika Sujay Rao, Pooja Suresh Yelkar, Omkar Narayan Pise, and Dr. Swapna Borde (2021) addressed medical gaps by developing a CNN model for skin disease detection using the Skin-Cancer-MNIST dataset. Their emphasis on efficient data preprocessing and human input underscored the importance of dataset quality in achieving accurate dermatological diagnoses [14]. Upma Yadav, Ashok Kumar, Anamika Tiwari, and Saurabh Mukherjee (2020) focused on early detection of skin cancers, aiming to improve treatment chances through their study on pre-processing techniques and automated classification methods. However, their approach may be limited to specific cancers, necessitating further exploration into broader applications [15]. Vijay Singh, KarthikeyanKaliyaperumal, MahyudinRitonga, and Malik Jawarneh (2023) contributed to the field by developing a comprehensive system for classifying skin disorders, integrating image preprocessing, augmentation, segmentation, and various algorithms for effective real-time disease detection. Their study showcased impressive accuracy rates, especially with support vector machine (SVM) reaching 98.8%, although algorithm dependency may hinder generalization [16]. MtendeMkandawire and Dr. GlorindalSelvam (2022) proposed a focused diagnosis system for skin disease using a Residual Neural Network (RNN) in MATLAB,achieving accurate predictions through weighted image classification. However, their reliance on MATLAB may limit accessibility for some users, highlighting the need for diverse toolsets in the field [17]. Sunpreet Bhatiya, Shubham Kasture, Saniya Shaikh, and Zuha Momin (2023) contributed by suggesting a machine learning system for skin disease diagnosis, targeting melanoma, eczema, and psoriasis. Their emphasis on preprocessing, feature extraction, and classification aimed to improve accuracy, particularly in regions with limited medical resources, although the system's accuracy may vary for different skin diseases [18]. Finally, Lubna Riaz, Hafiz Muhammad Qadir, Ghulam Ali, Mubashir Ali, and Muhammad Ahsan Raza (2023) proposed a robust skin disease detection system combining CNN and Local Binary Patterns (LBP) for impressive accuracy of 98.60% on the HAM10000 dataset. Their acknowledgment of potential overfitting and limitations in detecting other skin lesions demonstrates a comprehensive understanding of the challenges in the field [19]. ShengnanHao, Haotian Wu, Chengyuan Du, XinyiZeng, and ZhanlinJi (2023) introduced the CACDU-Net for skin lesion segmentation, focusing on enhancing diagnostic accuracy through effective ablation techniques and loss function optimization. However, their model's performance heavily relies on the quality and diversity of the dataset, emphasizing the need for comprehensive data collection and augmentation strategies [20].

3. MATERIALS AND METHODS

When it comes to identifying skin diseases, the Convolutional Neural Network (CNN) and You Only Look Once (YOLO) methodologies are comparable.

A.DATASET

Training and testing the models need a large dataset of skin photos that reflect a range of diseases and disorders. To ensure the accuracy and robustness of the model, this dataset should include a broad range of skin conditions. The suggested model was trained and validated using labelImg, which we utilized to annotate the images in the dataset some glimpse of which is shown in Figure 1.

Figure 1: Glimpse of data set

B. IMAGE PREPROCESSING

The dimensions of the input image must be fixed for the CNN and YOLO architectures. Consistent input dimensions speed up training by enabling CNN models to digest information more quickly and save computational overhead. This standardization ensures that the model can learn well, since CNN architectures typically anticipate a constant input size. Likewise, YOLO mandates that the input photos be downsized to a 448*448 resolution that matches the network architecture. However, resizing is done with the aspect ratio preserved to avoid distortion because YOLO views the entire image as a single unit. By ensuring that the input photographs can be efficiently divided into a grid of cells for object detection, this scaling improves the accuracy of the predictions.

C. MODEL ARCHITECTURE

A CNN architecture is created to recognize nine different kinds of skin conditions based on factors including the number of layers and how they are arranged, the activation functions, the learning rate, the number of training steps per epoch, and the optimizer. Four convolution layers, two max-pooling layers, a flattening layer, and three dense layers with Relu and SoftMax activation functions are used to implement the network as shown in the Figure 2. By applying filters to the input image, convolutional layers are able to extract hierarchical features such as textures and edges. Layers of pooling minimize spatial dimensions, maintaining significant information while lowering processing demand. The collected features are interpreted for classification using fully linked layers.

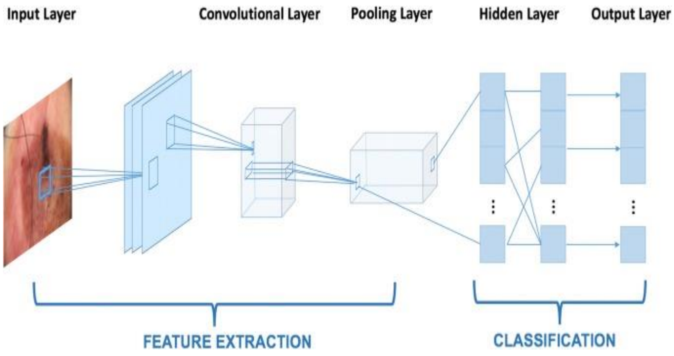

FIGURE 2: CNN Architecture

You Only Look Once, or YOLO This architecture does padding and maintains the aspect ratio while resizing a picture to 448 by 448 pixels. The CNN network then plays this image. There are 24 convolution layers in this model, followed by 4 max-pooling layers and 2 completely linked layers. First, we employ 1*1 convolution, which is followed by 3*3 convolution, to reduce the number of layers (or channels) as shown in Figure 3. With the exception of the final layer, which employs a linear activation function, the whole architecture of this architecture uses a leaky ReLU. Additionally, batch normalization aids in regularizing the model. Overfitting is also avoided by employing the dropout approach. Using, the input image is split into grid cells. YOLO determines the class probabilities and bounding boxes inside each grid cell after that. This technique works well for applications requiring the real-time identification of skin diseases since it analyzes the entire image in a single evaluation. It is also useful for applications that require rapid inference. The uniform design of YOLO also simplifies the training process and enhances overall performance.

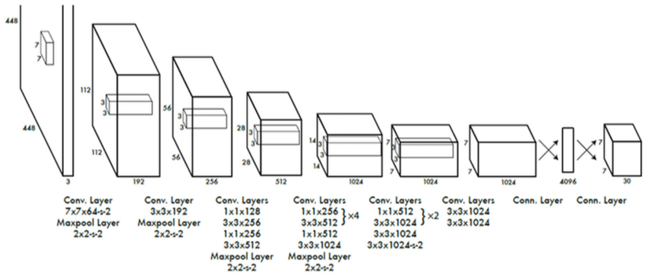

Figure 3: YOLO Architecture.

D. Training Procedure

There are several crucial elements in the CNN model training process when utilizing Keras. The first step in preparing the data is gathering skin photos and matching disease classifications, then preprocessing the images to improve uniformity and diversity. Subsequently, suitable model architectures are chosen by defining layers like Conv2D, MaxPooling2D, and Dense using Keras's high-level API. After that, the model is compiled in Keras with the optimizer, loss function, and optional metrics specified. Fit() is used to iterate over mini-batches of the training data during training. Keras does all internal training tasks, such as forward pass, loss computation, backpropagation, and parameter updates. Since the model is trained using labeled data, supervised learning is the learning strategy used. Following training, metrics like accuracy, precision, and recall are used to assess the model's performance on a different validation dataset. Finally, the model is tested using untested data to determine how well it performs in real-world scenarios.

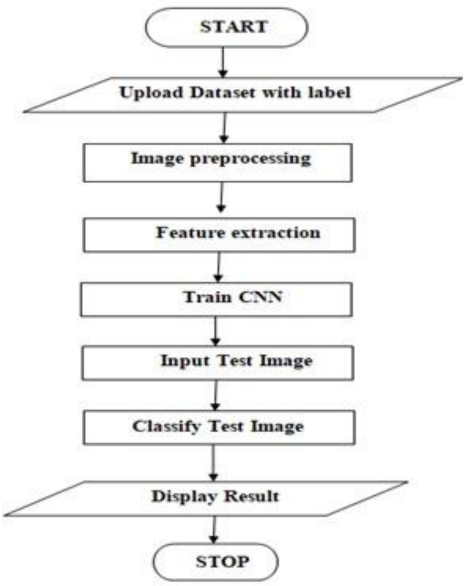

Figure 4: Flowchart of CNN

It uses YOLOv8m.pt for YOLO models. This is a reference to the YOLOv8 model that is used with the pre-trained weights (.pt file) in PyTorch (pt). The procedures in the training process are the same as for CNN models: preparation of the data, selection of the model architecture, optimization algorithms and loss functions, and evaluation. YOLO models, on the other hand, have a special architecture made for object identification tasks, including layers dedicated to object classification and bounding box prediction. In order to develop YOLO models, the pre-trained weights are usually adjusted using a specific dataset, maybe with the aid of transfer learning techniques. Furthermore, YOLO models are frequently Furthermore, due to their distinct architecture and object detection objective, YOLO models are frequently trained using a different training protocol than normal CNNs.

4. RESULTS

Model	Accuracy of Image	Accuracy of Live detection	Epoch	Learning rate
CNN	80.91%	60%	25	20 Min
YOLO	92%	90%	10	4.5 Hour

Table -1: Performance Comparison Table

i. RESULTS WITH CNN

The results produced by CNN model are also satisfactory. The possible precision with which a convolutional neural network (CNN) architecture used in Keras can classify skin diseases. The study achieves classification accuracies ranging from 70% to 80% by utilizing a dataset consisting of 468 photos that represent 8 different skin disorders,The findings highlight the significance of taking into account variables including image quality, dataset variety, preprocessing approaches, and model optimization strategies in order to provide precise classification results for skin diseases utilizing CNN architectures implemented in Keras model.Figure 5 shows the testing accuracy of17.5% and the training accuracy as 0.200%, and training loss of 0.5%, testing loss of 0.3%

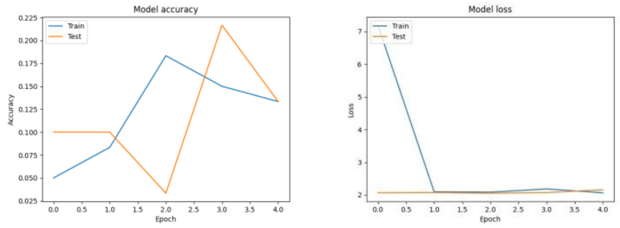

Figure 5: Model accuracy and loss of CNN

ii. RESULTS WITH YOLO

With a dataset of 468 photos covering 8 distinct diseases, the expected accuracy of using the YOLOv8m.pt architecture for skin disease classification is estimated to be between 75% and 90%. Several important elements are taken into consideration in this prediction. To begin with, the quality of the dataset is crucial, as better training results are produced by high-quality photos and precise categorization. Second, a diverse dataset one that includes a range of illness presentations, severities, and skin types—is essential for facilitating the model's ability to generalize to previously unobserved data. Thirdly, improving accuracy requires model optimization through the adjustment of parameters including learning rate, batch size, and augmentation strategies. Further improving the model's capacity to extract pertinent features from the data are appropriate preprocessing methods including normalization, scaling, and data augmentation.

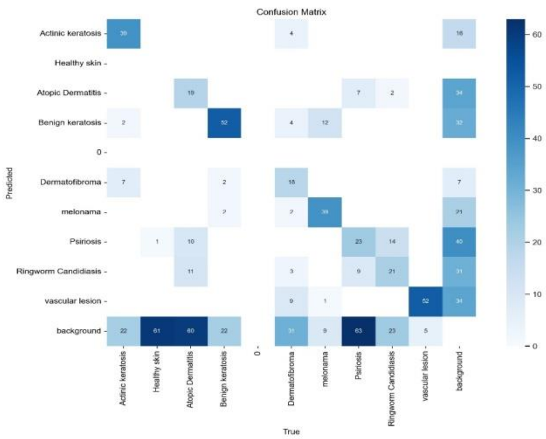

Figure 6: Confusion matrix

With rows denoting the actual classes or labels—Actinic keratosis, Healthy skin, Atopic Dermatitis, Benign keratosis, Dermatofibroma, Melanoma, Psoriasis, Ringworm Candidiasis, Vascular lesion, and Background—the confusion matrix that is provided provides a thorough overview of the performance of the classification modelas shown in figure 6. The projected classes or labels are indicated by the columns. The number of times the actual class (row) was predicted to be the associated predicted class (column) is shown by each cell in the matrix. Through close inspection of every cell, one can spot trends in both accurate and incorrect predictions, providing insight into which classes are frequently misunderstood. Making well-informed judgments to improve the model's classification skills and accuracy is made possible by this analysis.

I. **Snapshots of the user interface**

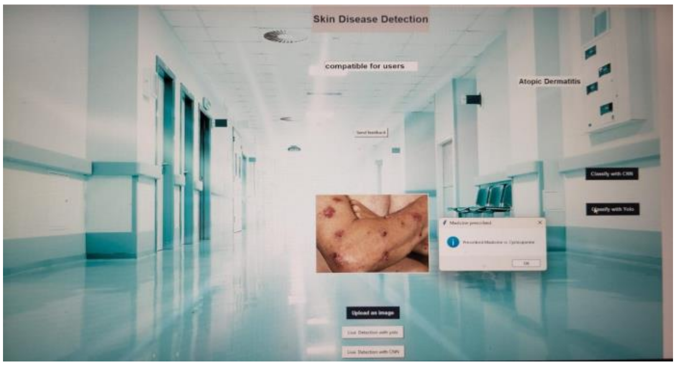

Figure 7: Classification of skin disease using CNN

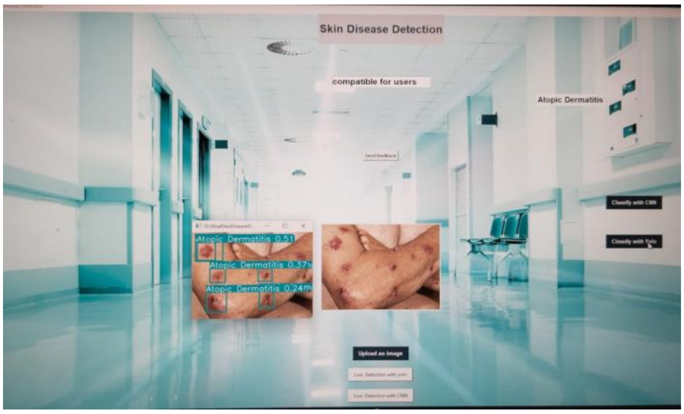

Figure 8: Classification of skin disease using YOLO

5. CONCLUSIONS

Skin diseases are defined as medical conditions that affect the skin and are typified by abnormal changes in appearance, texture, or color. These ailments might vary from common problems like eczema and acne to more dangerous ones like psoriasis or melanoma. Numerous reasons, such as autoimmune illnesses, genetic predispositions, environmental conditions, or infections, can lead to skin problems. Accurate diagnosis and therapy are essential for controlling and reducing skin disease symptoms. With an interface for entering symptoms and uploading images, Convolutional Neural Networks can accurately identify skin diseases. The technology seeks to improve accuracy by utilizing CNN's powerful picture recognition capabilities. Pre-processing for the best CNN training includes noise reduction, normalization, and scaling. To ensure better system performance, user feedback is gathered and used to optimize medicine recommendations. Using deep learning methods, the project seeks to improve overall health by facilitating early detection and precise diagnosis. Finally, patient opinions on the therapy options they were given will be gathered. With this, a suggestion system that assesses the system's efficacy and makes any required adjustments is built. The project's overarching goal is to help identify skin disorders early on and diagnose them accurately, which will ultimately improve patient outcomes and raise people's quality of life.

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