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Research Article

A YOLO-Powered Deep Learning Approach to Psoriasis Classification

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Abstract: With the rise of technological advancements, various clinical practices have undergone significant transformations. The field of dermatology, in particular, has experienced rapid progress. Skin ailments encompass a spectrum of conditions impacting the human body's largest organ. These conditions range in severity from mild instances like acne or eczema to more serious cases such as skin cancer or Psoriasis, which is a persistent inflammatory skin disorder affecting a considerable global population. The precise categorization and assessment of the severity of Psoriasis play a pivotal role in its effective treatment and management. Conventional classification methodologies often prove subjective, time-intensive, and susceptible to variations in interpretation amongst different observers. In contrast, machine learning and deep learning, subsets of artificial intelligence, are revolutionizing various domains by addressing diverse challenges autonomously, without the need for human intervention. AI technologies have opened up fresh avenues for the objective and automated classification of Psoriasis. However, these technologies are yet to attain their maximum potential in terms of accuracy. Here, we try to implement a relatively new method i.e., YOLO (You Only Look Once) which is basically an object detection technique, to try to classify psoriasis. A comparison of all the different models of YOLOv8 have been studied here. The study also deploys the Google Colab platform for computational needs and ease.

Keywords: Psoriasis, Classification, YOLOv8, Artificial Intelligence, Deep Learning, Dermatology, Google Colab

1. Introduction

Psoriasis is an immune-mediated disorder with an unknown cause that is characterized by abnormalities of the immune system, which causes inflammation within the body. There may be visible symptoms of infection, including raised plaques and scales on the skin. Among all the skin diseases, Psoriasis is the most widely affected chronic, recurrent, immune-mediated disease of the skin and joints. Psoriasis occurs because the immune system reacts rapidly, leading to rapid skin cell growth. Generally, normal skin sheds off and regrows in a month, but with Psoriasis, it does not shed but instead piles up on the skin surface. Plaques and scales can appear anywhere on the body, although they most frequently appear on the scalp, knees, and elbows [1].

When examining its global occurrence statistics, Psoriasis impacts approximately 2% of the worldwide population. As indicated in a research study led by April W Armstrong and colleagues, the incidences of psoriasis among adults in the United States stands at around 3%, encompassing an estimated 7.5 million individuals, with a higher incidence observed among individuals of Caucasian descent [2]. In contrast, statistics from India report a prevalence ranging from 0.44% to 0.28%. This variation can be attributed to the geographical proximity to the equator, with regions farther from the equator experiencing a greater prevalence [3].

Notably, individuals in their thirties and forties constitute the most significantly affected age group when it comes to Psoriasis. In terms of gender distribution, statistical data reveals that males are afflicted at a rate twice that of females. Additionally, scientific studies have substantiated the role of genetics in the occurrence of Psoriasis.

People suffering from Psoriasis can develop the risk of developing other severe disorders such as psoriatic arthritis, cardiovascular episodes, such heart attacks and strokes and issues with the mind include sadness, anxiety, and low self-esteem.

In addition to these conditions, individuals with psoriasis may face an elevated susceptibility to various health issues, including Crohn's disease, diabetes, metabolic syndrome, obesity, osteoporosis, uveitis (inflammation of the eye's central region), liver disease, and kidney disease.

Medical image classification studies using YOLO (You Only Look Once) are crucial in the healthcare domain as they provide efficient and real-time solutions for identifying and categorizing abnormalities in medical images. YOLO's ability to detect and classify multiple objects simultaneously within a single pass significantly accelerates the diagnostic process, aiding in timely medical interventions. This approach enhances the speed and accuracy of medical image analysis, contributing to early disease detection and improved patient outcomes.

2. Related Work

2.1 Types of Psoriasis

There are several types of Psoriasis, each with its distinct characteristics. Table I shows the major 6 types of Psoriasis, its characteristics, and the prevalence of each type [4]– [9].

Table 1. Characteristic of Psoriasis with approximate prevalence in affected population across the globe.

Characteristics	Prevalence
The predominant form of psoriasis is plaque psoriasis, characterized by the development of dry, itchy, elevated skin patches (known as plaques) covered with varying scales. These plaques typically manifest on the elbows, knees, lower back, and scalp.	80% of cases
Nail Psoriasis mostly affects finger and toe nails which causes pitting, abnormal growth of nails and discoloration. Sometimes Onycholysis may occur in psoriatic nails which is loosening and separation of nails from the nail bed.	50% of cases
Inverse Psoriasis predominantly impacts the cutaneous regions situated within the anatomic creases of the groin, buttocks, and mammary areas. It incites the development of erythematous, non-scaly plaques characterized by heightened susceptibility to exacerbation due to mechanical friction and increased perspiration. Fungal infections may trigger this type of Psoriasis.	>10% of cases
Guttate Psoriasis predominantly manifests in the demographic of young adults and paediatric individuals. Its typical provoking factor is commonly attributed to a bacterial infection, most notably streptococcal pharyngitis. Clinically, it is characterized by diminutive, teardrop-shaped, desquamating lesions localized on the trunk, upper limbs, or lower limbs, with a predilection for the central body region.	10% of cases
Erythrodermic Psoriasis, the rarest variant within the spectrum of Psoriasis, has the capacity to envelop the entire bodily surface with an exfoliating dermatitis, often accompanied by intense pruritus or a burning sensation. This condition can exhibit either a transient, acute course or persist as a chronic ailment. It causes lobster-like redness from head to toe, peeling, and scaling.	2% of cases
Pustular Psoriasis, an infrequent subtype, induces well-defined vesicles filled with purulent fluid. These vesicles can manifest as diffuse patches across the skin or localize to small regions on the palms or soles of the feet.	rare

There are other types of psoriasis which are also observed in patients but this study has considered the above six types mentioned in the Table 1 based on the prevalence and availability of the sample images. Figure 1 shows six types of psoriasis mentioned in Table 1

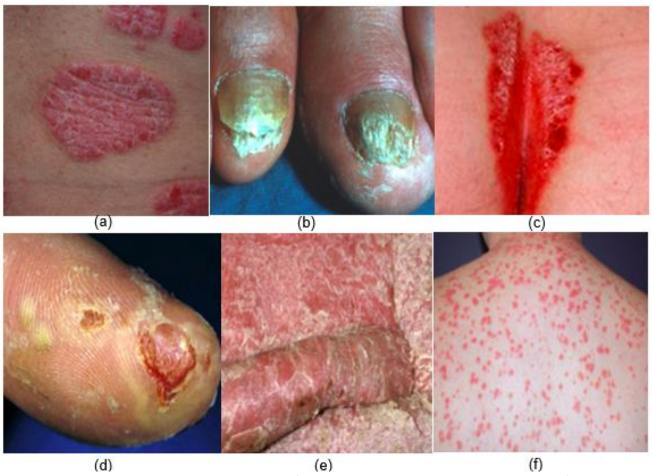


Figure 1. Shows the six types of Psoriasis sample images used for training the Deep Learning Model. (a) Plaque psoriasis (b) Nail psoriasis, (c) Inverse psoriasis, (d) Guttate psoriasis, (e) Erythrodermic psoriasis and (f) Pustular psoriasis.

2.2 AI in Healthcare

Artificial Intelligence is now being used in various healthcare applications such as data classification, precision medication, radiology, pathology, and drug discovery, where deep learning technology is actively used [10]. Diagnosing diseases is a major task that consumes most of the time and delays treatment in the process but use of Artificial Intelligence can replicate the diagnostic process and ease the diagnosis. To address issues with disease, medical data classification is used [11]. The healthcare industry primarily utilizes traditional machine learning in precision medicine, where treatment effectiveness for a patient is determined based on a multitude of patient characteristics and therapy context. Most machine learning and precision medicine applications require the use of supervised learning, which calls for a training dataset for which the possible outcome (such as the onset of disease) is known [12].

Under this Deep learning is the most sought-after domains, widely used for image dataset. Deep learning is applied in medical imaging, healthcare IT and other fields. Deep learning may help the healthcare personnel to identify the disease at early-stage and increase the efficiency.

Apart from the Deep learning traditional classification, YOLO which stands for You Only Look Once has proved to be quite an efficient model with additionally being 300 times faster than a Faster R-CNN. Broadly classifying there are two major types of detectors, namely, the single-stage detectors, which focus on all regions of the image for the possible detection of objects using a simpler architecture compared to the two-stage detectors which use a complex architecture [13]. The network is architecture is based on GoogleNet architecture. YOLO has different versions starting from the first version that was out in 2015. But different developed versions have a different backbone, which determines architecture. The latest one is the YOLOv8.

Though it's been 5 years since YOLO started, it still hasn't dealt with challenges like multi-scale training, Foreground-

Background class imbalance, Detection of smaller objects, large dataset, computational power, and Inaccurate localization during predictions [14]. Considering its popularity in other fields, YOLO is a very widely used object detection technique, but only some medical diagnosis experiments have been done so far.

Machine learning algorithms and deep learning models, such as convolutional neural networks (CNNs), have been employed to analyze medical images of psoriasis patients, including dermoscopy, clinical photographs, and histopathological images. The goal is to enhance the accuracy and efficiency of diagnosis [15], [16]. This is achieved by training a model using a labelled dataset, where inputs are paired with their corresponding outputs (classes). The trained model can then predict the class of new, unseen inputs, a process known as supervised learning.

Various methods can be utilized for the classification of psoriasis. In the case of CNNs, there have been numerous variations. For instance, experiments have been conducted to classify melanocytic skin lesions against healthy skin, resulting in models achieving accuracies of up to 82.4% [17]. Along similar lines, Nagina Amin et al. also utilized a CNN model but with different pre-trained networks for two and three classes, namely Psoriasis, normal skin, and other classes. Among the various pre-trained networks, ResNet yielded the best results, with an accuracy of 94% for two classes and 79% for three-class classifications [18]. Researchers have even attempted to classify different types of psoriasis. Syeda Fatima Aijaz et al. proposed a deep learning application for the sub-classification of various types of psoriasis using Python. They identified six classes: plaque, erythrodermic, guttate, nail, pustular, and normal skin. Two different algorithms were used: Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM). CNN achieved an accuracy of approximately 84.2%, while LSTM reached 72.3% [19]. This demonstrates the superior performance of CNNs in many cases.

PsLSNet is a network based on a modified U-Net architecture designed for automatically segmenting psoriasis lesions. The U-Net architecture comprises two paths: the contracting and expanding paths, forming a U-shape. It's a deep, fully convolutional network with 29 layers for extracting spatial information [20]. PsLSNet achieved an accuracy of about 94.80%.

In addition to CNNs, Vimal K. Shrivastava et al. introduced another method for automatically classifying images related to dermatological disorders, distinguishing between psoriatic lesions and healthy skin. They used an online accessible system based on dermatology Computer-Aided Diagnosis (CADx). The offline system trained with an SVM online classifier using a unique integrated feature space and dermatologist-derived ground truth [21]. Furthermore, the k-means clustering technique can be applied to the segmentation process and object tracking in color-skin images, with the addition of morphological reconstruction operations [22].

As per the survey, various methods have classified skin lesion or Psoriasis with normal skin. Only a few studies give the classification of different types of Psoriasis. These were majorly done on some pretrained models. One of the major drawbacks found was regarding the dataset which was not generalized. Secondly, these methods have a higher training time requirement due to higher computations. Our contributions made are as follows:

- Classification of six different types of psoriasis.
- Using YOLOv8 model for faster results.
- Implementing and comparing different YOLOv8

The rest of the article is as below. Section 2 discusses the methodology. Section 3 presents the results. Various discussions are made in section 4. Section 5 includes a brief conclusion.

3. METHODOLOGY

In this section, the research methodology employed to address the issues is discussed thoroughly. The goal is to offer a comprehensive and transparent explanation of the procedures undertaken to collect and analyse data. The Figure 2 shows the entire workflow of the proposed model. The section details about the data selection, data preprocessing, network selection and training attribute chosen for the study.

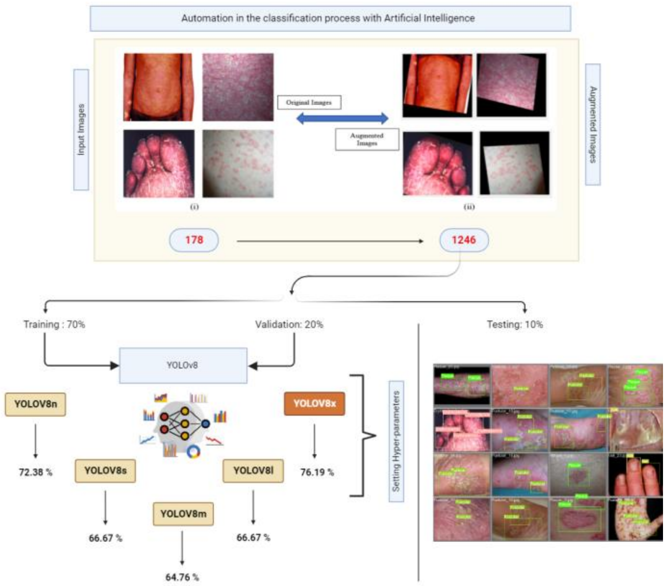


Figure 2. Workflow of the proposed method for classification of psoriasis images, it includes data set augmentation, training the YOLO (models) and validation with unused data set.

3.1 Dataset

Datasets play a crucial role in training and fine-tuning deep learning models. They serve as the foundation upon which these models learn patterns, relationships, and representations from the data. They provide the necessary training signal, enable model generalization, facilitate complex feature extraction, address bias, support transfer learning, and allow for evaluation and benchmarking. Several open access repositories are available for example Kaggle, medical ImageNet etc., that source for the images which most of the times labelled dataset. Here, we use a publicly available dataset and web scraping. The dataset was downloaded from DermNet repository [23]. This is an open-source repository which sources all the possible skin diseases that could exist. A total of 178 images were used.

3.2 Dataset augmentation

Augmentation is the process of artificially increasing the size of the dataset by introducing various predefined transformations such as random flipping, rotation, scaling, translation, enhancements, etc. The main idea behind performing such a procedure with the raw data is to improve the model's ability to perform well on unseen data by increasing the number of images and making the dataset more diverse. Following the augmentation process, the dataset size was significantly increased. The original dataset, with a 178 number of images, was expanded to a total of 1246 images. This expansion ensures that the model is trained on a more extensive and varied dataset, contributing to its adaptability to diverse input patterns.

3.3 Dataset preparation

Prior to the division into training, validation, and testing sets, the dataset underwent a preliminary preprocessing step. Images were systematically segregated into different subtypes, reflecting the diverse classes targeted for classification. This process involved organizing images into separate folders, each corresponding to a specific subtype. Such a meticulous organization facilitates targeted and efficient model training.

The entire pre-processed dataset was subsequently divided into three distinct sets: training, validation, and testing. This division is fundamental for assessing the model's performance, preventing overfitting, and gauging generalization capabilities. The training set comprises approximately 70% of the total data, while the validation set consists of the remaining 20%. This split ratio was carefully chosen to allocate a significant portion of the data for training, allowing the model to learn patterns and features, while still dedicating a substantial portion for validation to assess its performance on unseen but labelled data.

The testing dataset was intentionally kept entirely untouched during the entire training and validation process. This strategic decision ensures that the model's evaluation on the testing set reflects its performance on previously unseen data, providing a robust assessment of its real-world applicability.

3.4 Network

YOLO starts by dividing the input image into multiple grids. Each cell in the grid predicts a bounding box and a probability distribution over the possible object classes. The bounding box is represented by its center coordinates, width, and height. The probability distribution is a vector of length N, where N is the number of object classes. Each entry in the vector represents the probability that the cell contains an object of that class.

It is important because this algorithm enhances detection speed by enabling real-time object prediction. It constitutes a predictive method renowned for its precision, yielding highly accurate outcomes with minimal background noise. The algorithm possesses remarkable learning capabilities, allowing it to acquire and utilize object representations effectively within the context of object detection. The YOLO algorithm operates through the incorporation of three key techniques: Residual blocks, Bounding box regression, and Intersection Over Union (IOU).

Architecture

The YOLOv8 architecture comprises a convolutional neural network with distinct components: the backbone and the head. The head consists of numerous convolutional layers, succeeded by a sequence of fully connected layers. These layers play a crucial role in predicting bounding boxes, objectness scores, and class probabilities for identified objects within an image.The backbone on the other hand is the modified version of CSPDarkNet53 which uses a self-attention mechanism which enables the model to adapt its attention to various areas of the image and the prominence of various elements according on how relevant they are to the task at hand.

There are different models of YOLOv8 for classification trade off accuracy and speed. The smaller models are faster, but they are less accurate. The larger models are more accurate, but they are slower.

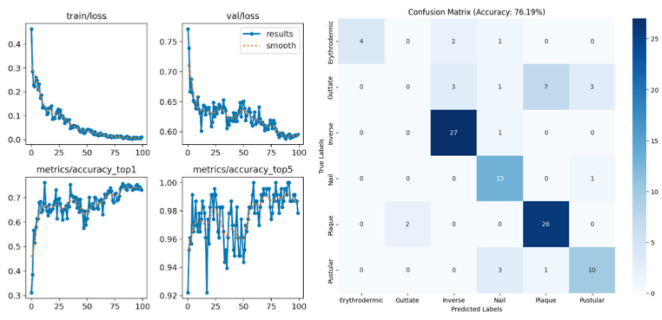
3.5 Training

The research utilized the Google Colab platform as the primary training environment. Google Colab among others also provides a cloud-based Jupyter notebook environment with free access to GPU resources, facilitating the training of deep learning models without the need for local GPU hardware. The Ultralytics training script was employed as the foundational framework for model training. Ultralytics offers a versatile and efficient platform for object detection and segmentation tasks. The provided training script served as the backbone, streamlining the training process and ensuring consistency across trials.

Training involved the use of a custom dataset tailored to the specific objectives of the study. The dataset was curated to encompass relevant features and variations necessary for the models to learn effectively. The dataset included corresponding labels. Each model was subjected to a distinct trial during the training process. The training process involved continuous monitoring of the custom dataset's performance, allowing for real-time adjustments and insights into the learning curves of the models. The training process for all five models ran consistently for 100 epochs. This decision was based on the trade-off between convergence and computational resources. The 100-epoch training scheme aimed to ensure that each model had sufficient exposure to the dataset for meaningful learning. The choice of multiple models enhances the robustness of the study and provides insights into the sensitivity of the results to different architectures and hyperparameters. It also allows for a more comprehensive evaluation of the models' generalization capabilities across diverse scenarios. Additionally, the use of distinct trials for each model served to minimize any potential bias introduced during the training phase.

4. Results and Discussion

A total of 5 sub-models of YOLOv8 were performed. For the ease of comparing, between the networks, we have kept the same set of augmented datasets, same randomization, same initial learn rate (0.001), same batch size (64) and same number of epochs (100). Training loss and validation loss are two essential metrics used in the training and evaluation of machine learning models, including neural networks like convolutional neural networks (CNNs) used in object detection tasks such as YOLOv8. These metrics help assess how well a model is learning from the training data and generalizing to unseen data. The training loss is a measure of how well a model is performing on the training data during the training process. It determines the error quantitatively between the model's predictions and the actual target values (ground truth) for the training examples. The validation loss on the other hand is a measure of how well a model generalizes to data that it has not seen during training. It estimates the error between the model's predictions and the actual target values for a separate dataset called the validation dataset. Because of the ability of the Python coding and Google Colab GPU environment, the time requirement to train a model reduced. It also facilitated direct testing of the network, i.e., not need to be exported every time as in MATLAB. The training loss, validation loss, accuracy plots of the best class and top 5 classes were obtained for five sub-models of YOLOv8 i.e., YOLOv8-n, YOLOv8-s, YOLOv8-m, YOLOv8-l and YOLOv8-x. The train and validation graphs of the x model are shown in the Fig. 2 (a) whereas (b) demonstrate the predicted labels in the form of confusion matrix.



(a) (b)

Figure 3. YOLOv8-x model's (a) training and validation graphs (b) Confusion Matrix for the performance measure of the model

Performance Evaluation

The highest accuracy was obtained by x model i.e., Extra-large model. The accuracy achieved is 76.19% for which true positive i.e. TP =80., Table 2 Shows the performance evaluation matrix for that.

The results obtained from the 100-epoch training were meticulously analyzed to identify any signs of overfitting or underfitting, ensuring the models achieved optimal performance without compromising computational efficiency. The number of true objects or instances in the dataset that the model should ideally detect or classify is termed as (N truth). These are the correct or actual objects present in the given data. Whereas the number of objects that the model has predicted or classified in the dataset is N(Classified). These are the objects that the model has identified, whether correctly or incorrectly. It is very starkly observed that the precision for guttate psoriasis is very poor in all the classification models we used. This can be attributed to limited dataset, poor feature representation, model complexity and clinical variability in observed cases of guttate psoriasis. However, the performance for other types of psoriasis classification was deemed satisfactory. The rigorous approach to training and evaluation can further contributes to the reliability and validity of the study's findings with bigger dataset, reinforcing the significance of the chosen methodology in achieving robust and insightful results.

Table 2. Performance Evaluation Matrix for YOLOv8x model

Class	N(Truth)	N(Classified)	Accuracy in %	Precision	Recall	F1-Score
Erythrodermic	4	7	97.14	0.57	1.0	0.73
Guttate	2	14	84.76	0.0	0.0	0.0
Inverse	32	28	94.29	0.96	0.84	0.90
Nail	19	14	93.33	0.93	0.68	0.79
Plaque	34	28	90.48	0.93	0.76	0.84
Pustular	14	14	92.38	0.71	0.71	0.71

Psoriasis is a long-lasting inflammatory condition that significantly impacts health-related quality of life and raises mortality and risk of malignant and cardiometabolic diseases. It affects people around the globe. According to a report by world psoriasis consortium 125 million people around the globe which is about 2-3% of the entire population have psoriasis. Many people suffering with psoriasis seek help from primary care providers. For recognition of psoriasis the diagnosis is primarily clinical and biopsy of the skin is hardly required but diagnosing the kind of psoriasis becomes a task. So, we try to facilitate timely diagnosis and appropriate management for intra-class classification of psoriasis with help of YOLO.

As of the present research, there is a noticeable gap in the existing literature concerning the application of YOLOv8 in the classification of psoriasis. This research aims to fill this void by exploring the effectiveness of YOLOv8 in addressing the specific challenges associated with psoriasis classification. The obtained results using YOLOv8 are deemed appreciable in the absence of prior work in this domain. The application of YOLOv8 to psoriasis classification represents a novel approach, and the achieved outcomes hold significance in advancing the understanding of how object detection models can be leveraged for medical image classification tasks.

All five models of YOLOv8 were employed in the study to conduct a comprehensive comparative analysis. YOLOv8, known for its efficiency in object detection tasks, it is adapted for the specific task of psoriasis classification. The YOLOv8 architecture facilitates the detection of relevant features in medical images, enabling a deeper understanding of the underlying patterns associated with psoriasis. The study was followed by a thorough comparison of their performance. This comparative analysis aimed to identify the model that best suits the task of psoriasis classification based on a set of predefined metrics. The results highlight a notable trend: as the size of the YOLOv8 models increases, there is a reduction in processing speed. This observation is in line with expectations, considering the computational demands associated with larger model architectures. Simultaneously, the results reveal that as the model size increases, there is a corresponding improvement in accuracy. This finding aligns with the general understanding in deep learning that larger models, often characterized by increased parameters, have a greater capacity to capture complex patterns in data.

Through the comparative analysis of the five YOLOv8 models, it was possible to discern nuances in their performance, identifying trade-offs between speed and accuracy. The evaluation criteria included precision, recall, F1 score, and computational efficiency. The findings suggest that the choice of the optimal YOLOv8 model for psoriasis classification depends on the specific requirements of the application. Researchers and practitioners may need to weigh the trade-offs between processing speed and classification accuracy based on the constraints and priorities of their use case.

The observed relationship between model size, speed, and accuracy provides valuable insights for future research in medical image classification. It prompts considerations about the scalability of object detection models in healthcare applications and opens avenues for fine-tuning model architectures to achieve a balance between computational efficiency and classification performance.

The Figure 4 shows the accuracy of five different YOLOv8 models on the classification task. The models are labelled "Nano", "Small", "Medium", and "Large" and “Extra-large”. The accuracy of each model is shown on the y-axis, and the type of model is shown on the x-axis. The Extra-large model due to its extra parameter advantage was able to perform better but at the cost of speed.

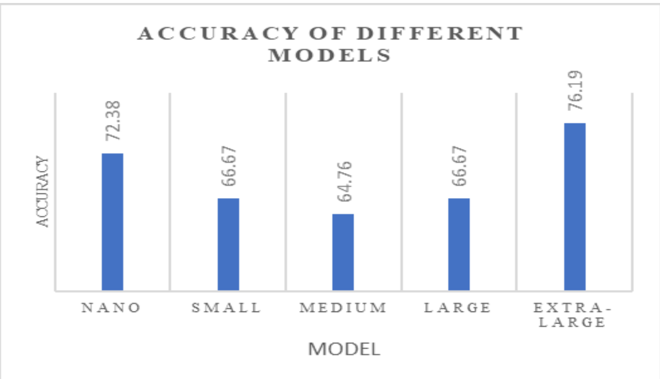


Figure 4 Comparative model of different YOLOv8 models with accuracies

6. Conclusion and Future Scope

Classification of Psoriasis as remained a problem ever since. With the latest technologies coming up in different fields, artificial intelligence has been heavily used in medical applications. We try to utilize this hype in the dermatology sector so as to aid the physician to determine the type of psoriasis. This paper has demonstrated the promising potential of utilizing YOLOv8, a cutting-edge object detection model, for the classification of Psoriasis, a chronic inflammatory skin disorder. Through meticulous experimentation and analysis, we sought to identify the best-performing variant among five distinct YOLOv8 models. The accuracy obtained was 76.19%, with the extra-large model. This paper hence represents a significant step forward in the application of deep learning and object detection techniques to dermatology, specifically in the context of Psoriasis classification. While challenges remain, the results achieved thus far hold promise for revolutionizing the diagnosis and management of Psoriasis and potentially other skin disorders. This work sets the stage for continued research and innovation at the intersection of artificial intelligence and healthcare. This work can be extended in future in different dimensions like multi-class classification of different dermatological condition with more enhanced dataset. As discussed in [24] real-time detection and processing will enhance the user experience. Collaboration and verification with dermatology experts will help improve the model, and further help in explainability and interpretability of the model. With these understanding integration of these models with electronic record systems could help in real time applications for primary identification.

Data Availability
Data will be made available by the corresponding author upon prior request

Conflict of Interest
Authors do not have any conflict of interest.

Funding Source
None

Authors’ Contributions
Author-1 researched literature, involved in protocol development, data analysis, wrote the first draft of the manuscript
Author-2 researched literature, and conceived the study involved in protocol development, data analysis, wrote the first draft of the manuscript.
All authors reviewed and edited the manuscript and approved the final version of the manuscript.

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