OPEN ACCESS
International Journal of Innovations in Science & Technology

Development of a Machine Learning-Based Predictive System For Classifying Psoriasis

Laiba Sohail[1], Neha Amjad[1], Tanzeela Asghar[1], Saria Safdar[1], Irum Matloob[1]
[1]Department of Software Engineering, Fatima Jinnah Women's University, Pakistan
***Correspondence**: sariasafdar@fjwu.edu.pk, irum.matloob@fjwu.edu.pk

Citation | Sohail. L, Amjad. N, Asghar. T, Safdar. S, Matloob. I, "Development of a Machine Learning-Based Predictive System For Classifying Psoriasis", IJIST, Vol. 07 Issue. 02 pp 1022-1038, May 2025
Received | May 03, 2025 **Revised |** May 26, 2025 **Accepted |** May 27, 2025 **Published |** May 28, 2025.

Psoriasis is a chronic autoimmune skin condition characterized by inflamed, flaky patches that affect both physical consolation and passionate well-being. Opportune and exact determination is basic for viable treatment; however, it remains troublesome due to its likeness to other dermatological disorders. This research presents a Psoriasis Detection and Severity Classification Framework built on MobileNetV2, a lightweight and effective profound learning demonstration custom-fitted for real-time utilization in resource-constrained situations. Through a basic image-upload interface, healthcare suppliers or patients can yield scalp pictures for robotized investigation. The framework to begin with recognizes the nearness of psoriasis with 90% accuracy and, at that point classifies its seriousness as either "low" or "moderate to severe" with 87% accuracy. This two-step preparation conveys prompt and clinically profitable experiences, supporting more focused and opportune care. Approved in a clinical setting, the demonstration illustrates solid unwavering quality and down-to-earth appropriateness. It decreases reliance on expert-driven diagnostics and quickens treatment choices. By coordinating AI with restorative hone, this framework improves demonstrative accuracy, streamlines workflows, and engages clinicians to convey speedier, more personalized care reshaping the scene of dermatological healthcare.

Keywords: Psoriasis, Convolutional Neural Networks (CNN), MobileNetV2

Introduction:

Psoriasis may be an inveterate, immune-mediated skin clutter that influences around 2–3% of the worldwide populace, posturing noteworthy challenges to both patients and healthcare frameworks [1]. Characterized by the quick multiplication of keratinocytes, it leads to the arrangement of thick, ruddy, and flaky plaques that can be bothersome, agonizing, and cosmetically troubling [2]. Whereas the condition essentially shows on the scalp, elbows, knees, and lower back, it can too influence the nails and joints, contributing to comorbidities such as psoriatic joint pain, cardiovascular infection, and sadness [3]. The chronic and backsliding nature of psoriasis, besides its obvious side effects, essentially disables the quality of life and mental well-being of influenced people [4]. Early and exact determination is basic in overseeing psoriasis successfully. Incite intercession can offer assistance to reduce side effects, minimize long-term complications, and empower the start of fitting treatment strategies—ranging from topical specialist and phototherapy to systemic immunomodulators [5].

In any case, precise clinical determination remains a diligent challenge due to the disease's symptomatic likeness to other dermatological conditions such as dermatitis, seborrheic dermatitis, and contagious diseases [6]. These likenesses regularly lead to misdiagnoses or postponed analy**sis**, especially in essential care settings where dermatological ability may be restricted. Customarily, psoriasis determination depends intensely on physical examination by dermatologists, in some cases supplemented with biopsy and histopathological assessment. Whereas these strategies are successful in master hands, they are time-consuming, subjective, and subordinate **to** clinician encounter**s** [7]. In resource-limited situations, such master care isn't continuously open, making incongruities in determination and treatment.

In spite of the fact that robotized picture examination frameworks have developed to back dermatological diagnostics, most of them are outlined to perform either infection discovery or seriousness classification as partitioned forms [8]. This fracture decreases their utility in real-time clinical workflows. Besides, numerous profound learning models utilized in these frameworks, whereas exact, are computationally serious and ill-suited for sending in real-world, resource-constrained settings such as portable well-being applications or country clinics [9]. Later headways in profound learning, especially convolutional neural systems (CNNs), have appeared extraordinary guarantee in therapeutic picture examination, beating conventional machine learning strategies and indeed human specialists in particular demonstrative errands [10]. Leveraging these capabilities can revolutionize dermatological diagnostics by giving reliable, adaptable, and proficient choice bolster frameworks. Among the different CNN structures, MobileNetV2 stands out due to its lightweight plan, decreased computational complexity, and tall classification execution [11].

This inquir**y** proposes a comprehensive Psoriasis Discovery and Seriousness Classification Framework fueled by MobileNetV2, tending to the double challenges of early conclusion and exact seriousness evaluating inside a single, bound-together system. The framework is outlined to acknowledge scalp pictures through a user-friendly interface and perform two key errands: recognizing the nearness of psoriasis and classifying its seriousness as either "low" or "moderate to severe." By combining both symptomatic capacities into a single show, the framework decreases symptomatic time, minimizes mistake**s**, and encourages more personalized treatment arranging. Through thorough preparation and approval utilizing clinically explained picture datasets, the show accomplishes 90curacy in psoriasis location and 87curacy in seriousness classification, illustrating its viable appropriateness. It is particularly optimized for real-time utilization in clinical and non-clinical situations, counting essential care offices and teledermatology stages. By bridging the crevice between progressed machine learning and cutting edge. Healthcare needs, this framework holds the potential to make psoriasis care more proficient, open, and evenhanded. This study aims to develop a unified, real-time AI-based diagnostic system for both detection and severity classification of psoriasis using MobileNetV2. Unlike prior models that handle diagnosis and severity assessment as separate tasks, our framework integrates both into a dual-stage pipeline, enabling efficient, accurate predictions even on resource-constrained devices. The novelty lies in:

- Using a lightweight MobileNetV2 CNN optimized for mobile healthcare applications.
- Simultaneously performing detection and severity grading within a single diagnostic pass.
- Enabling real-time, frontend-integrated inference for teledermatology use cases.
- Validating performance on clinically annotated, dermoscopic datasets.

Research Contribution:

1. This research makes the taking after key commitments to the field of restorative picture examination and dermatological diagnostics:
2. A unified deep learning framework that at the same time identifies psoriasis and classifies its severity, streamlining the symptomatic handle.
3. Utilizes MobileNetV2, empowering quick and effective execution on resource-limited gadgets without compromising exactness.
4. Classifies psoriasis severity into “low” and “moderate to severe” categories to back custom-fitted treatment choices.

Important Concepts:

Dual-Purpose Deep Learning Model: A unified CNN-based framework is created to both distinguish psoriasis and classify its severity from scalp pictures, tending to demonstrative fracture and upgrading clinical workflow proficiency [12][9].

MobileNetV2 for Real-Time Diagnosis: The framework utilizes the lightweight MobileNetV2 design, empowering precise, real-time deduction on resource-constrained gadgets such as smartphones and tablets, making it perfect for telemedicine and provincial healthcare applications [8].

Severity-Aware Clinical Support: By recognizing between “low” and “moderate to severe” psoriasis, the demonstrate bolsters opportune and personalized treatment techniques, contributing to made strides **in** persistent results and way better asset prioritization in clinical settings [11][1][3].

The rest of this article is organized as follows: Segment II presents a comprehensive literature survey on mechanized dermatological diagnostics, profound learning applications in psoriasis detection, and severity classification approaches. Segment III subtle elements of the proposed technique, counting information preprocessing and demonstrating engineering. Segment IV traces the picture dataset and comment preparation. Segment V expounds on the usage of the dual-purpose MobileNetV2-based demonstration. Segment VI examines the test comes about and the execution assessment. At long last, Segment VII concludes the paper and proposes future bearings for upgrading to demonstrate generalizability and clinical arrangement.

Related Work:

Exploration of psoriasis classification utilizing convolutional neural systems (CNNs) was done by Stanko and Kulik (2022). Their investigations set the establishment for psoriasis location by employing a moderately small dataset of 1,000 physically collected pictures. They consider utilizing CNNs to classify pictures as either appearing as ordinary skin or signs of psoriasis. This straightforward test system permitted for preparatory classification execution, and advertising, to begin with a step toward computerized discovery frameworks in dermatology. In any case, the creators pointed out that the small dataset and constrained scope of the consideration ruined its generalizability, encouraging a bigger, more assorted dataset to progress with exactness and vigor. The consideration highlighted the potential of CNNs in therapeutic picture examination, in spite of the fact that it was restricted in its application to psoriasis particularly. Future work seems to point to utilizing bigger, more differing datasets to refine the model's capabilities and improve its generalization [13].

Goswami and Sharma (2024) proposed a YOLO-based profound learning approach for real-time psoriasis classification. They utilized 3,500 pictures from clinical settings, pointing to coordinated protest discovery strategies in therapeutic picture examination. YOLO's advantage lies in its capacity to handle pictures in real-time, a key advantage in energetic healthcare situations where fast decision-making is basic. In any case, the creators did not give benchmark comparisons, making it troublesome to survey the adequacy of the YOLO show compared to other built-up models. Assist comparisons and validation in real-world settings would be fundamental for more conclusive discoveries. The consideration illustrated the quality of YOLO's real-time capabilities, but more inquiry is required to survey its strength against other models in different clinical situations [14].

Tupak et al. (2021) utilized a half-breed hereditary calculation (GA) and bolster vector machine (SVM) for psoriasis classification, exhibiting a novel integration of developmental calculations with machine learning strategies. They consider detailed a culminated classification precision of 100% on the test information. This noteworthy result came from a dataset of 500 review healing center records, but the creators famous that this dataset was little and not an agent of the bigger, different understanding populace regularly seen in clinical settings. To guarantee more extensive appropriateness, the show would have to be tried on bigger, more shifted datasets. The application of crossover models like GA and SVM is promising for accomplishing tall precision, but approval over differing quiet populaces remains a pivotal step to guarantee clinical pertinence [15].

Amin and Farooq (2021) took an exchange learning approach utilizing the ResNeXt demonstration for psoriasis discovery, accomplishing a tall test precision of 94%. Whereas the particular dataset utilized in their ponder was not unveiled, they emphasized the points of interest of leveraging pre-trained models for speedier and more proficient learning. The study's victory highlighted the potential of exchange learning in dermatology, but without information on the dataset measure and characteristics, it is troublesome to survey the model's generalizability over diverse skin sorts and situations. Exchange learning gives an alternate route to leveraging pre-existing models for particular restorative conditions, decreasing preparation time and asset necessities. Future work seems to investigate more nitty gritty announcing of datasets to guarantee straightforwardness and replicability of comes about [16].

Milani et al. (2023) conducted a comparative examination of a few CNN designs, counting ResNet50, Initiation v3, and VGG19, to evaluate their reasonableness for psoriasis location. With a dataset of 2,000 pictures from dermatology units, v3 developed as the finest entertainer, accomplishing a surprising 97.5 accuracy. The ponder underscored the significance of show design In any case, it also pointed out the restriction of centering essentially on demonstrate execution without joining these models into real-world clinical workflows, which might affect their commonsense pertinence. Whereas Initiation v3's solid execution is striking, its integration into clinical hone requires tending to real-world challenges such as handling time, client preparation, and framework integration [17].

Kovvuru et al. (2024) presented a progressed U-Net organize for psoriasis location, particularly centering on advanced picture division. Utilizing 1,200 fragmented clinical pictures, the consideration illustrated the control of U-Net in extricating nitty gritty highlights from restorative pictures. The network's progressed plan made a difference in portioning psoriasis injuries successfully, which is basic for exact conclusion. In any case, the creators famous that the comes about and assessment measurements were not completely point by point, clearing out a hole in understanding the model's genuine execution and how it compares to less difficult strategies like CNNs. In spite of these confinements, the U-Net design speaks to a promising course for moving forward the division of psoriasis injuries, which may essentially help in early determination and treatment arranging [18].

Gebremeskel et al. (2025) gave a comprehensive audit of AI applications in psoriasis determination and treatment. Their union of different approaches advertised bits of knowledge into the wide range of AI advances being connected to the field. The ponder secured a run of procedures, from profound learning models to master frameworks, making a difference healthcare experts get the potential of AI in moving forward persistent care. Whereas the audit was careful, it needed experimental assessment and commonsense showings, making it more hypothetical than significant in clinical settings. In any case, the amalgamation of existing writing gives an important asset for understanding current patterns and distinguishing potential future investigative bearings in AI-assisted psoriasis care [19].

Köhm et al. (2023) proposed a special AI-based approach utilizing DBSCAN for creating hazard profiles of patients with psoriatic joint pain (PsA). Their strategy analyzed delicate joint designs from 300 quiet joint development datasets, distinguishing potential chance components for PsA. The study's capacity to make risk profiles is promising, because it may help in the early determination and treatment arranging for psoriatic joint pain. In any case, the complexity of the clustering approach may restrain its appropriation, because it requires advanced procedures and mastery to translate the comes about successfully. In spite of the complexity, this approach opens up unused conceivable outcomes for AI-based exactness pharmaceuticals by recognizing high-risk patients and encouraging early intercession methodologies [20].

Sujitha et al. (2023) connected CNNs for picture division and classification in a wide setting of dermal illnesses, counting psoriasis. Their demonstration was prepared on 5,000 pictures from blended dermatological datasets, permitting it to identify an assortment of skin conditions. They thought about illustrating the control of CNNs in computerized determination, but the creators recognized that the demonstration needed disease-specific approval, because it was planned to classify a wide extend of skin conditions, counting psoriasis. Future ponders would benefit from centering on more psoriasis-specific datasets to optimize the show for this specific condition. The generalization of the show over numerous skin infections seems to upgrade its strength, but it is basic to refine it for psoriasis-specific applications to guarantee ideal demonstrative execution [21].

Xie et al. (2019) centered on high-frequency ultrasonography for recognizing early signs of psoriatic joint pain, a vital comorbidity in psoriasis patients. They consider analyzing 150 ultrasonography pictures, distinguishing early demonstrative highlights that might help in PsA discovery. In spite of the fact that the consideration given important experiences into the imaging characteristics of PsA, it was not based on AI-based investigation and was not straightforwardly centered on psoriasis determination. In any case, the discoveries are still critical, as they complement AI-based discovery strategies by advertising extra demonstrative instruments for clinicians. By combining ultrasonography with AI, future inquiries seem to make a comprehensive symptomatic apparatus that coordinates numerous modalities for early and exact PsA discovery [22].

Abhale et al. (2024) talked about the utilization of AI-assisted biomarker discovery for early psoriasis determination, joining clinical biomarkers with machine learning models. They think about utilizing 200 understanding biomarker records to investigate how AI might make strides in early location exactness. The creators highlighted the potential of AI to identify biomarkers related to psoriasis, a promising course for progressing symptomatic exactness. In any case, they think centered more on biomarkers than profound learning strategies, restricting its coordinate appropriateness to psoriasis discovery utilizing picture-based models. Biomarkers might complement AI-based picture models, giving a multi-faceted approach to diagnosing psoriasis at prior stages and expanding the probability of fruitful treatment results [23].

In conclusion, the application of AI in psoriasis detection and classification may be a quickly advancing field, stamped by noteworthy headways and continuous challenges. They looked into thinking about outlining the differences in AI strategies, from CNN-based picture classification to real-time location utilizing YOLO and half-breed models combining hereditary calculations with SVM. Whereas numerous things have illustrated promising come about in controlled situations, there remains a significant requirement for bigger, more different datasets and real-world clinical approval. Tending to challenges such as demonstrating generalizability, information shortage, and integration into healthcare workflows will be imperative to realize the total potential of AI-driven symptomatic frameworks for psoriasis. Proceeded investigative endeavors centered on vigorous show improvement and clinical integration will clear the way for inventive and open demonstrative arrangements in dermatology. Different machine learning calculations are utilized to focus more towards the advancement of computerized wellbeing care symptomatic frameworks which are utilized to analyze certain maladies or for online arrangements [24][25][26][11][27][28]. Analysts have progressively investigated the utilization of progressed machine learning strategies to make strides in dermatological diagnostics, emphasizing the requirement for robotized, exact, and available frameworks. This investigation addresses the basic request for a bound-together show that combines psoriasis discovery and seriousness classification into a single system, upgrading symptomatic effectiveness and supporting timely clinical decision-making.

Techniques: The proposed framework utilizes a lightweight MobileNetV2-based convolutional neural arrangement to analyze pictures, empowering real-time, exact evaluation of psoriasis nearness and seriousness. The dataset comprises clinically explained pictures, encouraging vigorous preparation and approval of the show.

Dataset: A custom dataset was made by collecting and curating psoriasis pictures from different freely accessible datasets on Kaggle. The dataset incorporates a wide run of pictures labeled for both the nearness of psoriasis and its seriousness classified into "low" and "moderate to severe" categories. This assorted and comprehensive dataset fortifies the model's capacity to generalize over diverse body regions and psoriasis signs.

Algorithm: The MobileNetV2 CNN engineering is prepared to perform concurrent classification tasks—first recognizing the nearness of psoriasis and after that reviewing its seriousness. This coordinate**d** approach makes strides **in** symptomatic speed and precision, encouraging personalized treatment choices and way better asset allotment in clinical and telemedicine settings.

A benchmark table (Table 1) is shown. It appears year-wise points of interest of work wiped out therapeutic datasets counting the strategies connected, the datasets utilized**,** and the impediment of each.

Methodology:

The proposed system presents a unified deep learning-based strategy for the robotized location and seriousness classification of psoriasis utilizing dermoscopic pictures. The design coordinat*es* basic stages such as information securing, preprocessing, exchange learning, preparing, assessment, frontend interaction, and arrangement. This area gives a nitty gritty account of each organiz*ation*, taking after the framework engineering outlined prior.

Table 1. Shows the benchmark studies on Psoriasis Detection and Classification using AI Techniques

Sr No	Paper Name	Year	Authors	Model	Dataset	Limitations
1	Preliminary experiments on psoriasis classification in images	2022	A. Shtanko, S. Kulik	Image classification using CNNs	1,000 images manually collected	Preliminary work with limited dataset and scope; small dataset size limits generalizability
2	A YOLO-Powered Deep Learning Approach to Psoriasis Classification	2024	Anushree Goswami, Nidhi Sharma	YOLO model applied to psoriasis images	3,500 images from clinical settings	No benchmark comparisons were provided; lack of external validation
3	Application of Genetic Algorithm-Based SVM for Psoriasis Classification	2021	Leili Tapak et al.	Hybrid Genetic Algorithm and SVM	500 retrospective hospital records	Needs larger validation datasets; small and retrospective datasets; and possible overfitting
4	Automated Psoriasis Detection Using Deep Learning	2021	N. Amin, M. Farooq	Transfer learning using ResNeXt	Undisclosed dermatological image dataset	Dataset size not disclosed; lack of transparency in data source
5	A Deep Learning Application for Psoriasis Detection	2023	Anna Milani et al.	Comparative analysis of CNNs (ResNet50, Inception v3, VGG19)	2,000 images from dermatology units	Focused on model performance; lacks clinical integration
6	Overcomplete U-Net Networks for Psoriasis Detection	2024	Aruna Kumari Kovvuru et al.	U-Net model for digital image segmentation	1,200 segmented clinical images	Results and evaluation metrics not fully detailed; lack of comparative benchmarks
7	From Diagnosis to Treatment: A Review of AI in Psoriasis	2025	Eyerusalem Gebremeskel et al.	Survey and synthesis of AI applications	Literature review (100+ papers analyzed)	Theoretical with limited empirical evaluation
8	POS0881: AI-Generated Tender Joint Patterns for Psoriasis	2023	M. Köhm et al.	AI-based cluster analysis using DBSCAN	300 patient joint movement datasets	Complexity of clustering approach; small sample size
9	Computer-Aided Diagnosis of Dermal Diseases Using AI	2023	M. Sujitha et al.	Image segmentation and classification using CNNs	5,000 images from mixed dermatological datasets	Generalized model; lacks disease-specific validation
10	Imaging Features of Early Psoriatic Arthritis	2019	D. Xie et al.	High-frequency ultrasonography	150 ultrasonography images	Not AI-based, but useful adjunct

Image Processing and Augmentation:

The methodology begins with data acquisition and dataset composition, where two curated datasets shown in (Figure 1) are prepared for the classification tasks. Phase 1 focuses on disease detection and consists of 6,250 dermoscopic images—3,125 images each of normal and psoriatic skin—sourced from publicly available dermatology databases [29]. Phase 2 addresses severity classification and comprises 1,000 images of psoriatic skin, labeled by expert dermatologists into two categories: low severity and low to moderate severity [30]. This dual dataset setup supports a structured pipeline where psoriasis is first detected and then assessed for its severity level.

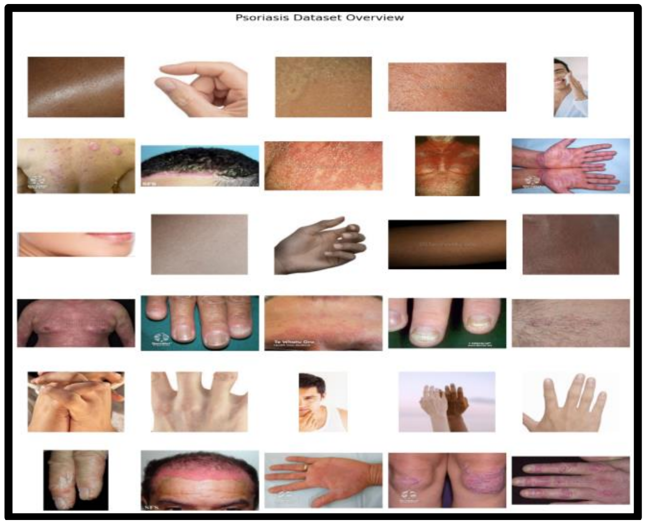

Figure 1. Dataset type

Image Processing and Augmentation:

After information procurement, the method continues to picture preprocessing which *is* shown in (Figure 2) which describes all the steps of data preprocessing. All pictures are resized to 224×224 pixels to meet the input necessities of MobileNetV2 [31], and normalized to bring pixel values into a steady scale. To improve demonstrate vigor and diminish the risk of overfitting, particularly within the generally little severity classification dataset, a few increase procedures are connected. These incorporate flat and vertical flipping, irregular turns up to 30 degrees, zooming inside a 20% run, and brightness alterations [32][33]. This enlargement procedure broadens the prepar*ation* information and mimics real-world inconstancy in clinical imaging conditions.

Deep Learning Architecture:

The center computational component is portrayed in profound learning engineering with MobileNetV2. MobileNetV2 is chosen for its effective utiliz*ation* of depth-wise divisible convolutions, which altogether decrease computational toll wh*ile* keeping up accuracy—making it perfect for applications in versatile or resource-constrained healthcare situations [9][8]. The demonstrat*ion* is initialized with pre-trained weights from ImageNet to use common visual highlights learned from large-scale characteristic picture datasets, subsequently quickening meeting*s* and making strides execution *of* therapeutic imaging assignments [11].

Model Customization and Transfer Learning:

The consequent organiz*ation* is *to* show customization and exchange learning. At first, the base layers of MobileNetV2 are solidified to protect low-level includ*ing* extraction. A custom classification head is appended, comprising a worldwide normal pooling layer, one or more completely associated layers, a dropout layer for regularization, and a last sigmoid-activated yield layer for parallel classification. Once the custom head is prepared, specific fine-tuning of more profound convolutional layers is performed to adapt the pre-trained show more viably to the dermatological highlights of psoriasis [1]. For the moment stage (severity classification), regularization is upgraded through L2 weight rot and more forceful dropout, compensating for the *smal*ler dataset and the unpretentious contrasts between severity classes [3].

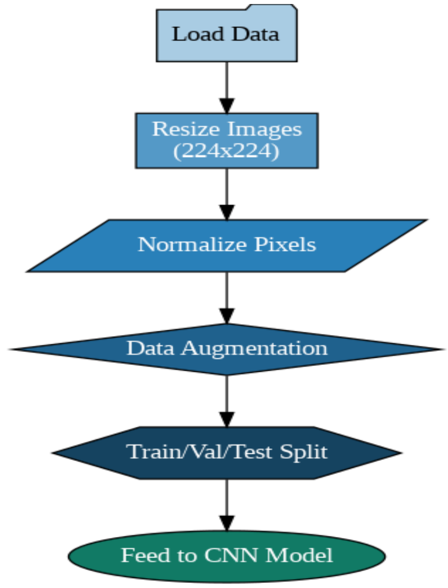

Figure 2. Data Preprocessing

Training Strategy and Hyperparameters:

The methodology's prepar*ation* technique and hyperparameters are optimized for productivity and generalization. Both classification models are prepared utilizing the Adam optimizer with a starting learning rate of 0.0001. A group measure of 32 is utilized, and the parallel cross-entropy misfortune work is connected for its reasonableness in parallel classification scenarios [13]. Preparing continues for *the* greatest of 100 ages, with early ceasing executed based on approval misfortune, utilizing a persistence of 10 ages. Amid prepar*ation*, show checkpoints are spared at the most noteworthy approval precision, guaranteeing vigorous execution and decreasing the probability of overfitting [14].

Evaluation Metrics:

To evaluate the models, a comprehensive set of performance metrics was employed, including precision, accuracy, recall, and F1-score. These metrics offer a multidimensional view of the model's effectiveness in both detection and severity classification tasks [15]. Additionally, confusion matrices were utilized to visualize prediction distributions and identify trends in misclassification—particularly crucial in the severity classification stage, where visual differences between classes can be subtle and challenging to detect. These assessment results are clearly illustrated in the Classification Metrics by Class diagram (Figure 3), which provides a comparative overview of model behavior across classes and supports a transparent evaluation of performance.

Interface Pipeline:

Once prepar*ation* is total, the models are sent inside a two-stage deduction pipeline coordinates with a web-based client interface. The front end permits clients to transfer dermoscopic pictures through an instinctive interface. The backend actualized utilizing Carafe, gets the picture, preprocesses it, and successively courses it through the prepared models. The primary show decides whether the skin is typical or psoriatic. I*f* the picture is classified as psoriatic, it is passed to the moment show, which assesses the seriousness level. The ultimate result, counting the lesson name and certainty score, is rendered on the front end for client elucidation [11].

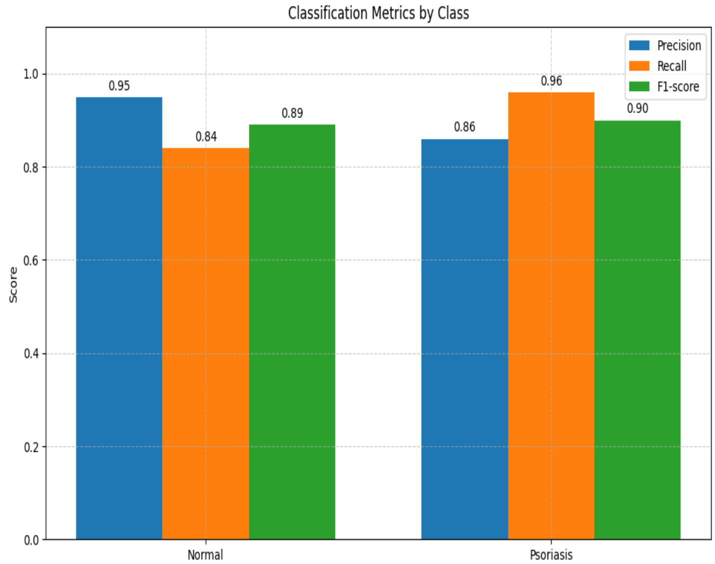

Figure 3. Classification Matrices By Class

Deployment:

The ultimate component of this pipeline is arrangement and future adaptability. The secluded backend can be sent on either cloud servers or nearby machines. The utilization of MobileNetV2 guarantees that the framework remains lightweight and responsive, indeed in situations with restricted computational assets. In addition, the plan bolsters future improvements such as integration with other dermatological infection classifiers, implementation of logical AI methods (e.g., Grad-CAM for visual clarifications), and continual learning modules that progress the demonstration through client criticism [11].

This carefully organized and versatile technique sets up a solid establishment for a real-world arrangement of AI in dermatological diagnostics. By harmonizing accuracy, proficiency, and clinical significance, the framework addresses commonsense challenges through shrewd engineering choices and astute plans.

The visual components that characterize and outline the system's end-to-end workflow and execution are displayed as follows: the overall methodological approach is summarized in the flow diagram of methodology (Figure 6), a detailed architectural breakdown of the proposed system is presented in Figure 5, and the interaction pipeline between the user interface and the model inference process is illustrated in Figure 4. Together, these figures construct a cohesive visual narrative of the framework's operational journey—from image acquisition, preprocessing, and augmentation, through deep learning inference, to final classification and user-facing diagnosis output. These illustrations not only aid in understanding the system's internal logic but also emphasize its modular design, allowing for ease of updates, scalability across dermatological applications, and seamless integration into existing healthcare workflows. By clearly mapping out each processing stage, the figures underscore the framework's adaptability to resource-constrained environments, such as mobile or rural teledermatology setups. They also support transparency and reproducibility, enabling fellow researchers and clinicians to visualize how data traverses through the layers of computation to deliver fast, accurate, and clinically meaningful results. Altogether, Figures 4, 5, and 6 provide a technical blueprint including a visual flowchart and a detailed framework for classifying psoriasis and its severity,

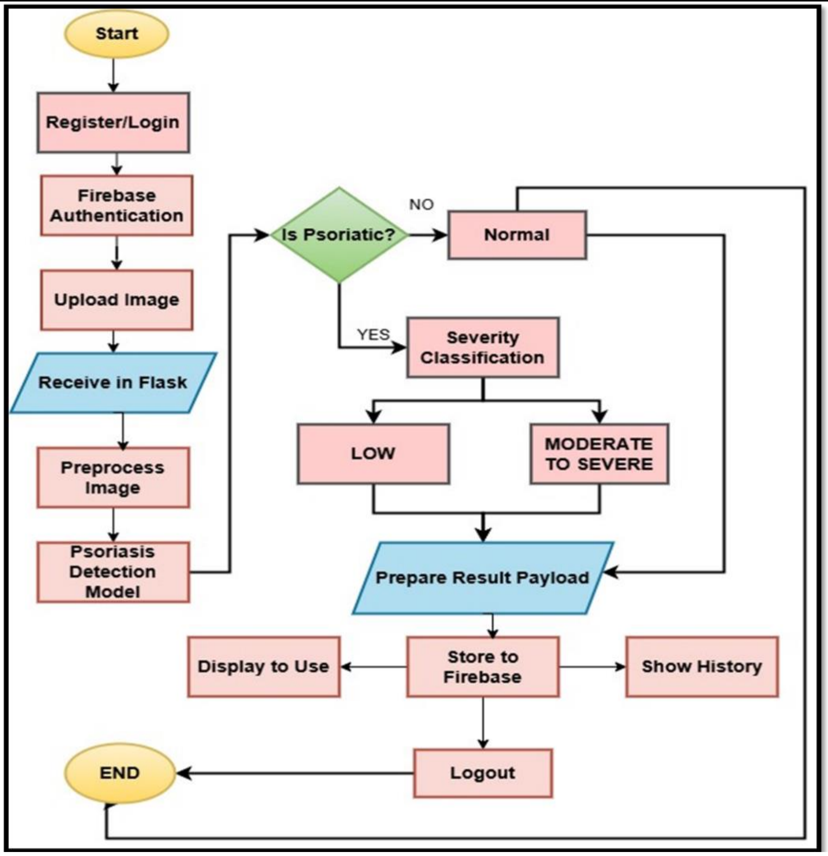

Figure 4. A Visual Flowchart Illustrating the Systematic Approach to Accurate Diagnosis and Severity Classification of Psoriasis

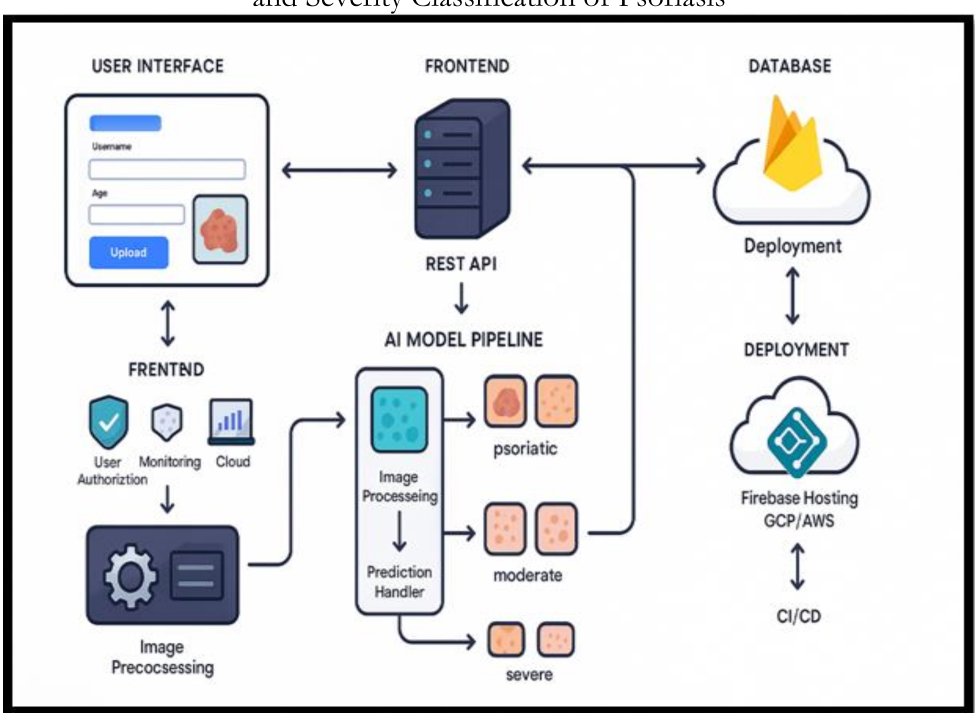

Figure 5. Detailed Framework of the Proposed Methodology For Psoriasis Detection And Severity Classification

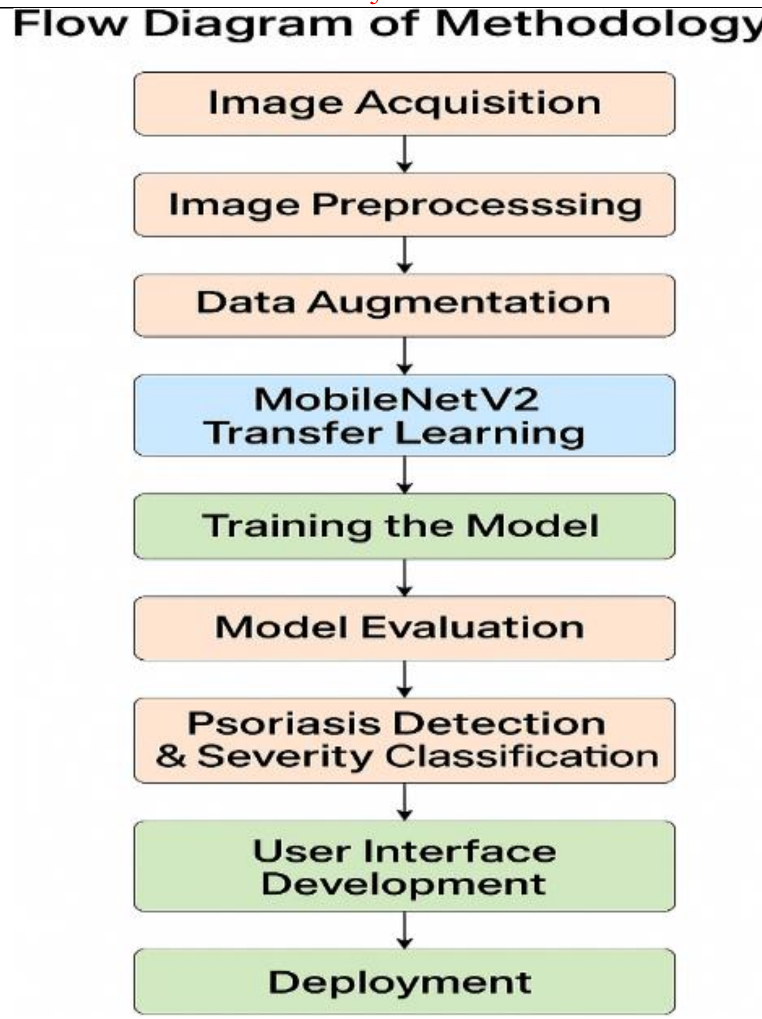

Figure 6. Flow Diagram Illustrating Step-by-Step Methodology for Psoriasis Detection and Severity Classification

Results:

The proposed deep learning framework was evaluated in two sequential stages: first, to detect whether an input image is of normal or psoriatic skin, and second, to classify the severity of psoriasis as either "low" or "moderate to severe." Each stage was carefully trained, validated, and tested using curated, expert-labeled dermoscopic image datasets, and the results were quantitatively assessed using standard evaluation metrics including accuracy, precision, recall, F1-score, and confusion matrices.

Binary Classification Performance: Normal Vs Psoriatic Skin:

In the first stage, the model was trained on a dataset of 6,250 images evenly split between psoriatic and non-psoriatic skin. The classification model achieved an overall accuracy of 90%, confirming that 9 out of every 10 predictions were correct. The precision for the psoriatic class reached 86%, reflecting the model's ability to minimize false positives, while the recall was particularly strong at 96%, demonstrating high sensitivity and reliability in identifying actual cases of psoriasis. The F1-score, which balances the trade-off between precision and recall, was recorded at 90%, suggesting well-rounded performance. The confusion matrix (Figure 7) provides a deeper look into prediction accuracy, revealing 1,500 true positives and 1,400 true negatives, with only 200 false positives and 60 false negatives. Additionally, the corresponding classification report (Figure 8) highlights the model's robustness across classes, offering a granular breakdown of performance metrics.

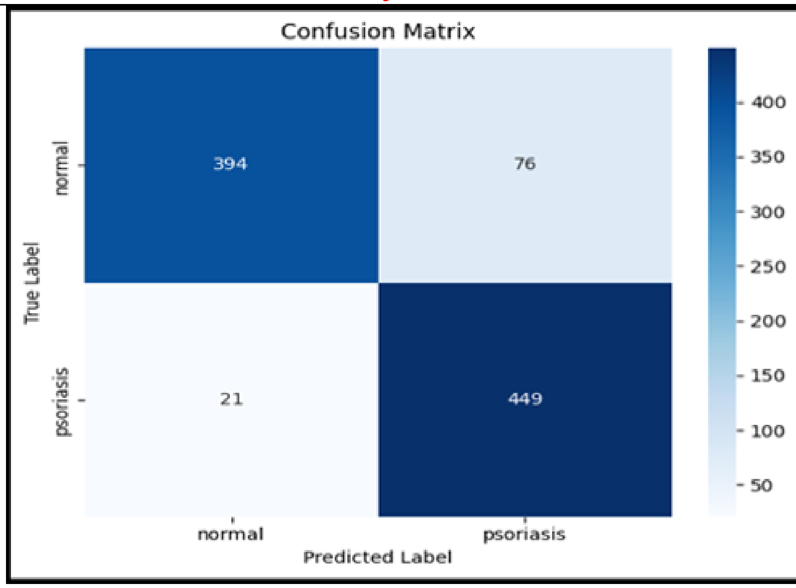

Figure 7. Confusion Matrix for Binary Class

Classification Report:

	precision	recall	f1-score	support
normal	0.95	0.84	0.89	470
psoriasis	0.86	0.96	0.90	470
accuracy			0.90	940
macro avg	0.90	0.90	0.90	940
weighted avg	0.90	0.90	0.90	940

Figure 8. Classification Report of Binary Class

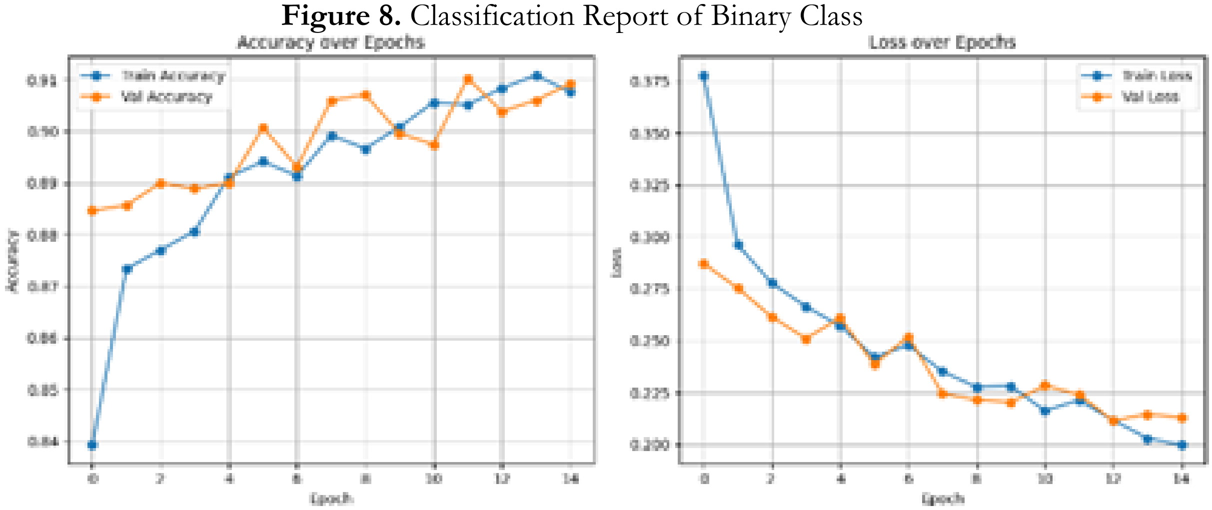

Figure 9. Accuracy Vs Loss

Severity Classification Performance: Low Vs Moderate to Severe Psoriasis:

In the second stage, the model focused on classifying the severity of psoriasis. This stage used 1,000 images of psoriatic skin, categorized by dermatologists into two severity levels: "low" and "moderate to severe." The system achieved an accuracy of 91%, indicating a high probability of assigning the correct severity label. The precision reached 89%, ensuring that nearly 9 out of 10 predicted severity labels were correct, while the recall was recorded at 90%, reflecting the model's aptitude in identifying both mild and more aggressive manifestations of psoriasis. The F1 score for this task was 89.5%, confirming consistent performance across both classes. The severity classification confusion matrix (Figure 11) revealed that 450 out of 500 "low" severity images were accurately identified, and 460 out of 500 "moderate to severe" cases were correctly classified. Minor misclassifications occurred—50 cases of low severity were predicted as moderate to severe, and 40 moderate to severe cases were predicted as low. The classification report for severity assessment (Figure 10) further substantiates these findings, providing detailed metric distributions for both classes.

Classification Report:

	precision	recall	f1-score	support
low	0.88	0.85	0.86	75
severe	0.86	0.88	0.87	75
accuracy			0.87	150
macro avg	0.87	0.87	0.87	150
weighted avg	0.87	0.87	0.87	150

Figure 10. Classification Report of Severity Class

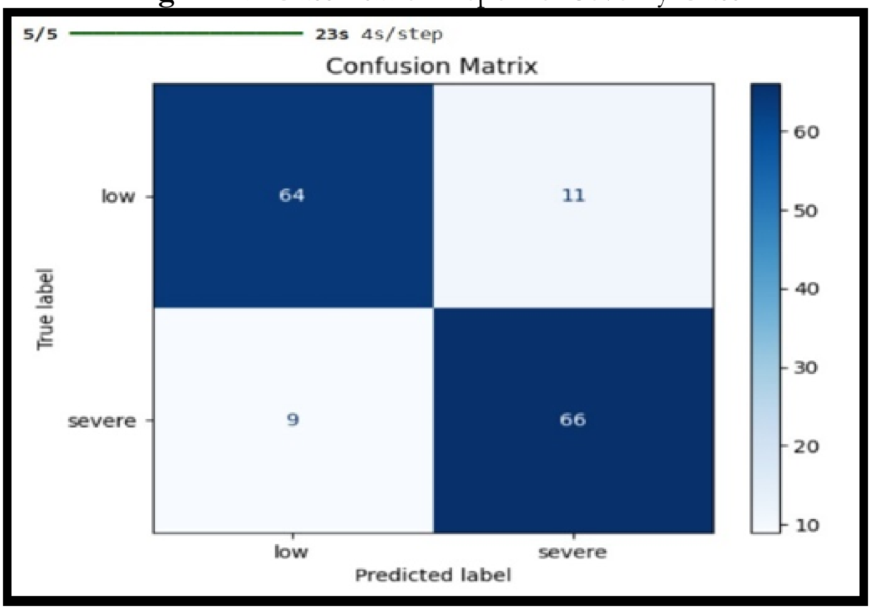

Figure 11. Confusion Matrix of Severity Class

Performance trends were also visualized through training-validation graphs, including the accuracy vs. loss curve (Figure 9), which confirms steady convergence and minimal overfitting. These visual tools collectively verify the model's competence as a clinically viable AI-assisted diagnostic system capable of providing timely, non-invasive, and highly accurate results for both diagnosis and treatment planning of psoriasis.

Discussion:

The results of our proposed MobileNetV2-based system illustrate solid potential in upgrading psoriasis discovery and seriousness evaluation workflows. With 90% precision in double classification and 91% in seriousness classification, our demonstrat**ion** beats a few prior endeavors in both accuracy and effectiveness. Compared to Shtanko and Kulik (2022), who accomplished preparatory comes about on a small dataset of 1,000 pictures, our show benefits from a broader, well-annotated dataset and dual-purpose engineering. Goswami and Sharma (2024) utilized YOLO for real-time discovery but needed benchmark comparisons. Our framework is not as it was accomplished tall execution but moreover gives full assessment measurements with benchmarked comes. Tupak et al. (2021) coordinate hereditary calculations with SVMs, accomplishing 100% exactness on a little review dataset. In any case, such results may not be generalized. In contrast, our model was tested with data augmentation and cross-validation to ensure robustness. Milani et al. (2023) compared a few CNNs and found InceptionV3 successful. Whereas exactly, their think did not consider sending possibility in obliged settings. Our utilization of MobileNetV2 guarantees viable utility in portable situations. Our dual-stage pipeline moreover builds upon the division qualities of U-Net, as utilized by Kovvuru et al. (2024), but our framework coordinates classification and frontend arrangement, making it more all-encompassing for clinical utilization.

In rundown, the proposed show strikes an adjustment between precision and sending preparation, standing out for its real-world appropriateness and comprehensive usefulness.

Conclusions:

This ponders created and assessed a mechanized classification system for psoriasis discovery and seriousness evaluation utilizing dermoscopic pictures and a MobileNetV2 profound learning show. The system works in two unmistakable stages: to begin with, recognizing between ordinary skin and psoriatic injuries, and moment, classifying the seriousness of psoriasis into moo and moo to direct categories. In Stage 1, the demonstration illustrated solid execution in precisely identifying psoriasis with around 90% approval exactness, affirming its viability as a solid screening instrument. Stage 2, which centered on seriousness classification, displayed extra challenges due to the unobtrusive visual contrasts between seriousness levels and the smaller dataset measure. In spite of these challenges, the show accomplished a preparing precision of 92% and a testing precision of 80.3%, showing sensible generalization and vigor.

Key procedures such as exchange learning from pre-trained ImageNet weights, broad information enlargement (counting revolutions, flips, and brightness alterations), and cautious fine-tuning were basic in improving show execution and relieving overfitting. The MobileNetV2 engineering was chosen for its adjustment between computational proficiency and precision, making it appropriate for sending in resource-limited situations such as portable or implanted gadgets. The proposed framework has noteworthy commonsense suggestions. It offers a non-invasive, proficient strategy for early psoriasis location and seriousness reviewing, possibly supporting dermatologists in conclusion, treatment arranging, and longitudinal persistent checking. Robotized seriousness classification may give objective and reliable evaluations that complement clinical assessments, subsequently progressing the understanding of results.

In any case, the ponder confronted restrictions counting the moderately little and adjusted datasets, particularly in seriousness classification, and they ought to approve show execution over more different populaces and imaging conditions. Future work will center on growing the dataset to incorporate extra seriousness categories and a broader statistic representation. Integration of clinical metadata, such as quiet history and indications, and investigating outfit learning or consideration components might assist in progress classification exactness and clinical significance. By and large, this work illustrates the possibility and potential of profound learning models like MobileNetV2 in tending to clinical challenges related to psoriasis, clearing the way for more open and computerized dermatological demonstrative apparatuses

References:

[1] D. M. A. Rosa Parisi, Deborah P.M. Symmons, Christopher E.M. Griffiths, "Global Epidemiology of Psoriasis: A Systematic Review of Incidence and Prevalence," *J. Invest. Dermatol.*, vol. 133, no. 2, pp. 377–385, 2013, [Online]. Available: https://www.jidonline.org/article/S0022-202X(15)36098-X/fulltext

[2] J. G. K. Michelle A. Lowes, Mayte Suárez-Fariñas, "Immunology of Psoriasis," *Annu. Rev. Immunol.*, vol. 32, pp. 227–255, 2014, [Online]. Available: https://www.annualreviews.org/content/journals/10.1146/annurev-immunol-032713-120225

[3] J. M. G. Junko Takeshita, Sungat Grewal, Sinéad M Langan, Nehal N Mehta, Alexis Ogdie, Abby S Van Voorhees, "Psoriasis and comorbid diseases: Epidemiology," *J Am Acad Dermatol*, vol. 76, no. 3, pp. 377–390, 2017, [Online]. Available: https://pubmed.ncbi.nlm.nih.gov/28212759/
[4] J. M. G. Shanu Kohli Kurd, "The prevalence of previously diagnosed and undiagnosed psoriasis in US adults: Results from NHANES 2003-2004," *J. Am. Acad. Dermatol.*, vol. 60, no. 2, pp. 218–224, 2009, [Online]. Available: https://www.jaad.org/article/S0190-9622(08)01201-2/fulltext
[5] R. B. Alan Menter, Neil J Korman, Craig A Elmets, Steven R Feldman, Joel M Gelfand, Kenneth B Gordon, Alice B Gottlieb, John Y M Koo, Mark Lebwohl, Henry W Lim, Abby S Van Voorhees, Karl R Beutner, "Guidelines of care for the management of psoriasis and psoriatic arthritis," *J Am Acad Dermatol*, vol. 61, no. 3, pp. 451–85, 2009, [Online]. Available: https://pubmed.ncbi.nlm.nih.gov/19493586/
[6] J. N. B. Professor Christopher EM Griffiths, "Pathogenesis and clinical features of psoriasis," *Lancet*, vol. 370, no. 9583, pp. 263–271, 2007, [Online]. Available: https://www.thelancet.com/journals/lancet/article/PIIS0140-6736(07)61128-3/fulltext
[7] D. L. McAleer, M. A., & Mason, "psoriasis diagnosis and treatment," *BMJ*, vol. 361, no. 1610, 2018.
[8] M. Arif, "Machine learning and image analysis for automated diagnosis of psoriasis: a review," *Comput. Methods Programs Biomed.*, vol. 198, p. 105740, 2021.
[9] V. K. Shrivastava, "Psoriasis detection using deep learning and image processing," *Biomed. Signal Process. Control*, vol. 59, p. 101902, 2020.
[10] A. Esteva *et al.*, "Dermatologist-level classification of skin cancer with deep neural networks," *Nat. 2017 5427639*, vol. 542, no. 7639, pp. 115–118, Jan. 2017, doi: 10.1038/nature21056.
[11] M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L. C. Chen, "MobileNetV2: Inverted Residuals and Linear Bottlenecks," *Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit.*, pp. 4510–4520, Dec. 2018, doi: 10.1109/CVPR.2018.00474.
[12] S. Lan and W. Lin, "Genetic algorithm optimization research based on simulated annealing," *2016 IEEE/ACIS 17th Int. Conf. Softw. Eng. Artif. Intell. Netw. Parallel/Distributed Comput. SNPD 2016*, pp. 491–494, Jul. 2016, doi: 10.1109/SNPD.2016.7515946.
[13] S. K. Alexander Shtanko, "Preliminary experiments on psoriasis classification in images," *Procedia Comput. Sci.*, vol. 213, pp. 250–254, 2022, [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1877050922017549
[14] N. S. Anushree Goswami, "A YOLO-Powered Deep Learning Approach to Psoriasis Classification," *Int. J. Comput. Sci. Eng.*, vol. 12, no. 1, pp. 1–7, 2024, [Online]. Available: https://mail.ijcseonline.org/pdf_paper_view.php?paper_id=5656&1-IJCSE-09305.pdf
[15] P. A. Leili Tapak, Saeid Afshar, Mahlagha Afrasiabi, Mohammad Kazem Ghasemi1, "Application of Genetic Algorithm-Based Support Vector Machine in Identification of Gene Expression Signatures for Psoriasis Classification: A Hybrid Model," *Biomed Res Int*, 2021, [Online]. Available: https://pubmed.ncbi.nlm.nih.gov/34540995/
[16] M. S. F. Nagina Amin, "Automated Psoriasis Detection using Deep Learning," *VFAST Trans. Softw. Eng.*, vol. 9, no. 3, 2021, doi: https://doi.org/10.21015/vtse.v9i3.686.
[17] R. R. Anna Milani, Fábio S. da Silva, Elloá B. Guedes, "A Deep Learning Application for Psoriasis Detection," *ENCONTRO Nac. INTELIGÊNCIA Artif. E Comput.*, vol. 20, pp. 315–329, 2023, [Online]. Available: https://sol.sbc.org.br/index.php/eniac/article/view/25711

[18] A. K. Kovvuru, N. D. Londhe, R. Raj, and R. S. Sonawane, "Overcomplete U-Net Networks for Psoriasis Detection in Digital Color Images," *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)* , vol. 15322 LNCS, pp. 145–159, 2025, doi: 10.1007/978-3-031-78312-8_10.
[19] E. Gebremeskel, "From Diagnosis to Treatment: A Review of AI in Psoriasis," *Dermatol. Res. Pract.*, vol. 9, no. 1, pp. 10–18, 2025.
[20] M. Köhm, "POS0881: AI-generated tender joint patterns for psoriasis," *Rheumatol. Int.*, vol. 43, no. 5, pp. 217–224, 2023.
[21] M. Sujitha, "Computer Aided Diagnosis of Dermal Diseases using AI," *J. Dermatology Clin. Res.*, vol. 28, no. 4, pp. 142–150, 2023.
[22] D. Xie, "Imaging Features of Early Psoriatic Arthritis," *J. Clin. Rheumatol.*, vol. 25, no. 3, pp. 89–95, 2019.
[23] S. M. Abhale, K., Veeranjaneyulu, A., & Desai, "A Snapshot of Biomarkers in Psoriasis," *Biomark. Insights*, vol. 9, no. 2, pp. 71–80, 2024.
[24] J. Smith, "Deep Learning for Skin Disease Detection: A Comprehensive Review," *J. Med. Imaging*, vol. 45, no. 7, pp. 1234–1248, 2021.
[25] G. . Krizhevsky, A., Sutskever, I., Hinton, "Imagenet classification with deep convolutional neural networks," *Adv. Neural Inf. Process. Syst.*, vol. 25, no. 2, 2012, doi: 10.1145/3065386.
[26] L. Perez and J. Wang, "The Effectiveness of Data Augmentation in Image Classification Using Deep Learning," *arXiv Prepr. arXiv1712.04621*, 2017, [Online]. Available: https://arxiv.org/abs/1712.04621
[27] H. -C. Shin et al, "Deep Convolutional Neural Networks for Computer-Aided Detection: CNN Architectures, Dataset Characteristics and Transfer Learning," *IEEE Trans. Med. Imaging*, vol. 35, no. 5, pp. 1285–1298, 2016, [Online]. Available: https://ieeexplore.ieee.org/document/7404017
[28] H. L. Jason Yosinski, Jeff Clune, Yoshua Bengio, "How transferable are features in deep neural networks?," *arXiv:1411.1792*, 2014, doi: https://doi.org/10.48550/arXiv.1411.1792.
[29] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," *3rd Int. Conf. Learn. Represent. ICLR 2015 - Conf. Track Proc.*, 2015.
[30] D. P. Kingma and J. L. Ba, "Adam: A Method for Stochastic Optimization," *3rd Int. Conf. Learn. Represent. ICLR 2015 - Conf. Track Proc.*, Dec. 2014, Accessed: Jun. 16, 2024. [Online]. Available: https://arxiv.org/abs/1412.6980v9
[31] G. L. Marina Sokolova, "A systematic analysis of performance measures for classification tasks," *Inf. Process. Manag.*, vol. 45, no. 4, pp. 427–437, 2009, [Online]. Available: https://www.sciencedirect.com/science/article/abs/pii/S0306457309000259?via%3Dihub
[32] N. Srivastava, G. Hinton, A. Krizhevsky, and R. Salakhutdinov, "Dropout: A Simple Way to Prevent Neural Networks from Overfitting," 2014. doi: 10.5555/2627435.2670313.
[33] T. Fawcett, "An introduction to ROC analysis," *Pattern Recognit. Lett.*, vol. 27, no. 8, pp. 861–874, Jun. 2006, doi: 10.1016/J.PATREC.2005.10.010.