Literature Review (First Research) Template

Guide Name	**Mrs.G.Sowmya**
Student Name	**S.Poojitha,M.Akshitha Reddy,K.Shruthi,K.Mahesh Raju**
Project Topic Title	**AI-Driven Assistant for Rapid Dermatology Triage**

1		
Reference in APA format		
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
https://arxiv.org/abs/1808.03426	H. L. GURURAJ 1 , (Senior Member, IEEE), N. MANJU 2 , A. NAGARJUN2 , V. N. MANJUNATH ARADHYA3 , AND FRANCESCO FLAMMINI 4 , (Senior Member, IEEE)	Skin cancer, segmentation, deep learning, CNN, Densenet169, Resnet50.
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)	**The Goal (Objective) of this Solution & What is the problem that need to be solved**	**What are the components of it?**
The current solution is the **DeepSkin** model, which utilizes deep learning techniques for skin cancer classification.	The DeepSkin model aims to improve the early detection and classification of skin cancer using deep learning techniques, particularly Convolutional Neural Networks (CNNs). The primary problem it addresses is the difficulty dermatologists face in distinguishing between benign and	The components include the dataset, preprocessing, segmentation, feature extraction, and classification.

	malignant skin lesions, which can lead to late diagnoses and poor patient outcomes. By automating the classification process, DeepSkin seeks to enhance diagnostic accuracy, streamline workflows for healthcare professionals, and ultimately increase survival rates for patients with skin cancer.	

The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process

The **DeepSkin model** utilizes deep learning techniques, particularly Convolutional Neural Networks (CNNs), to enhance the early detection and classification of skin cancer from dermatoscopic images.

	Process Steps	**Advantage**	**Disadvantage (Limitation)**
1	Feature Extraction	This step significantly reduces the need for manual feature engineering and improves the model's ability to learn complex patterns	CNNs require substantial computational resources and large labeled datasets for effective training.
2	Classification	Transfer learning allows for faster training and improved accuracy by leveraging pre-trained models.	If the pre-trained model is not appropriately fine-tuned, it may carry over biases that affect classification performance.

Major Impact Factors in this Work
The major impact factors in the DeepSkin model include dataset quality and diversity for effective training, the use of Convolutional Neural Networks (CNNs) for enhanced feature extraction, and the implementation of data pre-processing techniques like noise removal to improve image clarity.

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
The classification accuracy of skin lesions, which is influenced by various factors in the model.	The type of Convolutional Neural Network (CNN) architecture used (e.g., DenseNet169, ResNet50), which directly affects feature extraction and classification performance.	The quality and diversity of the dataset (HAM10000), which can enhance or diminish the model's ability to generalize across different skin lesion types.	: The data pre-processing techniques applied (e.g., noise removal, sampling), which influence the effectiveness of feature extraction and ultimately impact classification accuracy.

Relationship Among The Above 4 Variables in This article

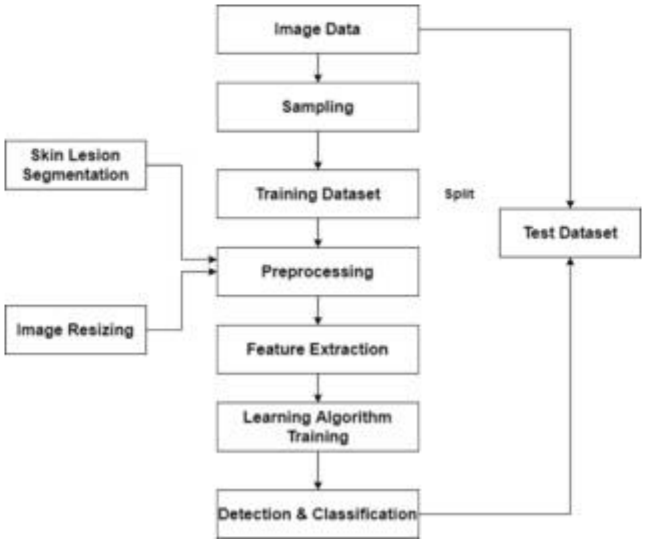
Input and Output	Feature of This Solution	Contribution & The Value of This Work
The input for the DeepSkin model consists of dermatoscopic images from the The output of the DeepSkin model includes the predicted classifications of	The features of the DeepSkin solution include the integration of the HAM10000 dataset for diverse skin lesion representation, the application of Convolutional Neural Networks (CNNs) like DenseNet169 and ResNet50 for robust feature extraction, and advanced pre-processing techniques such as the Dull Razor method for noise reduction, which	The major impact factors in the DeepSkin model include dataset quality and diversity for effective training, the use of Convolutional Neural Networks (CNNs) for enhanced feature extraction, and advanced pre-processing techniques like the Dull Razor method for noise reduction, which collectively enhance the model's accuracy in skin cancer classification.

HAM10000 dataset, which includes 10,015 images of various skin lesions	skin lesions, providing a detailed assessment of the types of skin cancer present in the input images, along with accuracy metrics that reflect the model's performance during testing, such as precision, recall, and F1-score.	collectively enhance the model's accuracy in skin cancer classification.	

Positive Impact of this Solution in This Project Domain	**Negative Impact of this Solution in This Project Domain**
The **DeepSkin solution** enhances precision in skin cancer diagnosis and classification, supporting early detection and improving treatment outcomes while advancing research in dermatological imaging and deep learning methodologies.	The negative impact of the DeepSkin solution includes increased data complexity, which can complicate model training and interpretation, as well as the risk of overfitting due to reliance on a limited dataset, potentially leading to poor generalization on unseen data. Additionally, the model demands high computational resources, which may limit accessibility for smaller research facilities and hinder real-time application in clinical settings.

Analyse This Work By Critical Thinking	**The Tools That Assessed this Work**	**What is the Structure of this Paper**

The DeepSkin model proposes a deep learning approach for skin cancer classification, effectively utilizing Convolutional Neural Networks (CNNs) to enhance diagnostic accuracy while addressing challenges such as data imbalance and noise in dermatoscopic images. By employing advanced pre-processing techniques like the Dull Razor method for hair removal and leveraging the HAM10000 dataset, the model aims to improve feature extraction and classification performance.	Convolutional Neural Networks (CNNs): Used for effective feature extraction and classification of skin lesions. Transfer Learning: Implemented with models like DenseNet169 and ResNet50 for improved performance. Data Pre-processing Techniques: Such as the Dull Razor method for noise removal to enhance image quality. .	i)Abstract ii). Introduction iii). Literature Review iv). Methodology v) Results and Discussion vi) I. Conclusion
Diagram/Flowchart		



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Reference in APA format	

<table>
<tr><th>URL of the Reference</th><th>Authors Names and Emails</th><th>Keywords in this Reference</th></tr>
<tr><td>https://doi.org/10.1016/j.imu.2023.101311</td><td>Debarpan Das ,Elcin Ergin,Bruno Morel,Michelle Noga,Derek Emery,Kumaradevan Punithakumar</td><td>Skin moles, dermatology, neural networks,Nested hierarchical transformer, Model, triage system.</td></tr>
<tr><th>The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)</th><th>The Goal (Objective) of this Solution & What is the problem that need to be solved</th><th>What are the components of it?</th></tr>
<tr><td>AI-assisted mole detection using a transformer-based algorithm.</td><td>The objective of this study is to identify the presence of moles in dermatological images uploaded by patients for online triage in telemedicine settings. This approach addresses the critical need for early detection of moles, which is essential for facilitating timely diagnosis and treatment of potential skin cancers, such as melanoma. By employing advanced AI techniques, the solution aims to provide immediate feedback to patients, enabling them to seek further medical consultation when necessary, thus improving overall patient care and outcomes in dermatology.</td><td>NesT Model: A nested hierarchical transformer network for mole detection.

Teledermatology Platform: Allows patients to upload images for analysis.</td></tr>
<tr><th colspan="3">The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process</th></tr>
<tr><td colspan="3">The NesT model processes images to detect moles, providing immediate feedback that can help prioritize cases for dermatologists. This aids in efficient triaging and follow-up treatment procedures.</td></tr>
</table>

	Process Steps	Advantage	Disadvantage (Limitation)

1	Image Upload by Patients	Patients can easily upload images for analysis from home, increasing accessibility to dermatological care.	Potential variability in image quality based on patient-uploaded photos.
2	Mole Detection with NesT Model	High accuracy in detecting moles enables timely referrals to dermatologists for further evaluation.	Requires sufficient training data to maintain accuracy; may struggle with rare or atypical mole presentations.
3	Triage System Implementation	Flags images with detected moles for prioritization in follow-up consultations with dermatologists.	Dependence on technology may lead to over-reliance on AI without thorough human oversight in diagnosis.

Major Impact Factors in this Work

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
Detection of skin moles	Images uploaded by patients	Image quality affecting detection accuracy	Feedback mechanism guiding patient referrals based on results.

Relationship Among The Above 4 Variables in This article

Input and Output	Feature of This Solution	Contribution in This Work
	This solution utilizes a NesT model (Nested hierarchical transformer) to detect moles in	This solution enhances early detection of skin conditions by enabling patients to self-assess

Input	Output

<table>
<tr>
<td><table><tr><td>Dermatological images uploaded by patients for analysis.</td><td>Detection alerts indicating the presence of moles and recommendations for dermatologist consultation.</td></tr></table></td>
<td colspan="2">dermatological images uploaded by patients. The model integrates advanced neural network techniques to enhance the accuracy of mole detection, providing immediate alerts to patients if a mole is identified. This functionality serves as a triage system, allowing dermatologists to prioritize cases for further examination and treatment, thereby improving patient access to timely dermatological care.</td>
<td>their lesions through an AI-driven platform, potentially improving outcomes and reducing healthcare burdens.</td>
</tr>
<tr>
<th colspan="2">Positive Impact of this Solution in This Project Domain</th>
<th colspan="2">Negative Impact of this Solution in This Project Domain</th>
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<tr>
<td colspan="2">Facilitates quicker access to dermatological assessments and improves the efficiency of healthcare delivery by prioritizing urgent cases.</td>
<td colspan="2">Challenges include ensuring consistent image quality and addressing potential over-reliance on AI for diagnosis without adequate human review.</td>
</tr>
<tr>
<th>Analyse This Work By Critical Thinking</th>
<th colspan="2">The Tools That Assessed this Work</th>
<th>What is the Structure of this Paper</th>
</tr>
<tr>
<td>The study highlights the importance of integrating AI into telemedicine to improve patient outcomes while acknowledging the limitations and challenges associated with technology-driven healthcare solutions.</td>
<td colspan="2">NesT Model: For mole detection.
Deep Learning Algorithms: Compared against other models like ViT and Inception-v4.
Dataset Sources: Combination of private clinical images and publicly available datasets for training and validation.</td>
<td>1. Abstract
2. Introduction
3. Related Works
4. Materials and Methods
5. Results</td>
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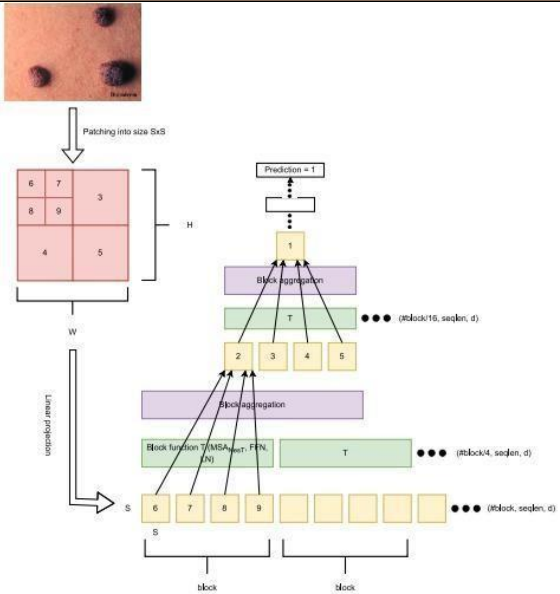
Diagram/Flowchart


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3		
Reference in APA format		
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
https://www.frontiersin.org/journals/artificial-intelligence/articles/10.3389/frai.2020.543405/full	ADAM BAKER , YURA PEROV, KATHERINE MIDDLETON, JANIE BAXTER, SAURABH JOHRI.	Virtual Assistant, AI Diagnosis, Triage, symptom checker, computer-assisted diagnosis.
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)	**The Goal (Objective) of this Solution & What is the problem that need to be solved**	**What are the components of it?**
The current solution proposed in the reference is "The Babylon Triage and Diagnostic System "uses a Bayesian Network to model medical conditions and their relationships.	The goal of the Babylon Triage and Diagnostic System is to provide accurate and timely medical advice to patients, improving access to healthcare and reducing the burden on healthcare systems. The problem addressed by this system is the challenge of providing reliable medical advice, especially in remote or underserved areas, where access to healthcare professionals may be limited. Additionally, the system aims to reduce unnecessary healthcare utilization by providing accurate self-triage advice	Knowledge Base,Natural Language Processing (NLP) Bayesian Network,Machine Learning Algorithms, User Interface
The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process		

	Process Steps	Advantage	Disadvantage (Limitation)
1	Data Collection	Ensures high-quality input data, enabling the model to learn effectively from relevant features, like a valid data.	Time-consuming and , requires expert validation.
2	Bayesian Network Construction and Triage Decision-Making	Captures complex disease-symptom relationships and Optimizes patient outcomes through expected harm minimization.	Requires careful parameterization to avoid overfitting and May be conservative, leading to higher care referrals.
3	Evaluation using Clinical Vignettes	Offers realistic testing against human diagnoses.	Restricted to pre-set cases, limiting real-world diversity.

Major Impact Factors in this Work

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
Diagnostic and triage accuracy	Patient symptoms	Regional disease prevalence	Bayesian network model

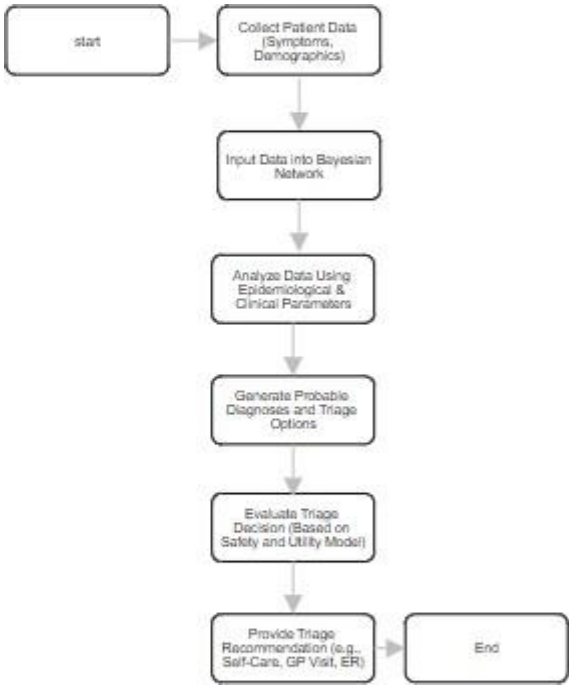
Relationship Among The Above 4 Variables in This article

Input and Output	**Feature of This Solution**	**Contribution & The Value of This Work**
<table><tr><th>Input</th><th>Output</th></tr><tr><td>Patient symptoms, demographics, and regional epidemiological data.</td><td>Triage advice (e.g., "visit ER" or "self-care") and potential diagnoses.</td></tr></table>	The Babylon Triage and Diagnostic System features a Bayesian Network that provides region-specific, personalized triage advice by modeling complex disease-symptom relationships. It emphasizes patient safety, offering human-comparable accuracy in diagnosis and triage, and is designed to be explainable and adaptable across various healthcare environments.	The Babylon system presents a novel AI-based solution for healthcare triage, offering an accessible means for symptom assessment, particularly valuable in areas with limited healthcare access. By providing a model with human-comparable accuracy, this study underscores the potential for AI to augment, rather than replace, clinical expertise.

Positive Impact of this Solution in This Project Domain	**Negative Impact of this Solution in This Project Domain**
Enhanced access to care, increased diagnostic accuracy, and support for overloaded healthcare systems.	Potential over-reliance on AI, with risks of misdiagnosis if human oversight is reduced in critical cases.

Analyse This Work By Critical Thinking	**The Tools That Assessed this Work**	**What is the Structure of this Paper**
The paper evaluates an AI-powered triage system against human doctors, demonstrating the AI's potential to provide accurate diagnostic and triage recommendations. Utilizing a Bayesian Network model, the Babylon Triage and Diagnostic System simulates patient interactions, revealing comparable accuracy and safety to human practitioners, which is crucial for enhancing healthcare delivery.	Babylon Triage and Diagnostic System Role-Play Experimental Paradigm Conditional Probability Tables (CPTs)	1. Abstract 2. Introduction 3. Materials and Methods 4. The Babylon Triage and Diagnostic System 5. Experimental Paradigm 6. Results 7. Conclusion

Diagram/Flowchart



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4		
Reference in APA format		
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
https://jesr.ub.ro/1/article/view/287	Benjamin O. ADEGOKE, Kehinde A. SOTONWA, Lawrence O. OMOTOSHO, Oluwashina A. OYENIRAN,Joshua O. OYENIYI	Dermatology, Artificial Intelligence, Diagnosis, Skin Diseases,Medical Technology, Acute Skin Problems Chronic Diseases, Recognition Accuracy
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)	**The Goal (Objective) of this Solution & What is the problem that need to be solved**	**What are the components of it?**
The current solution used in the study is: "An Automated Skin Disease Diagnostic System based on a Deep Learning Model" (AlexNet)This system applies Convolutional Neural Networks (CNNs), specifically the AlexNet architecture, to classify and diagnose skin diseases. The model employs transfer learning to improve classification accuracy on dermatological images, thus	**Goal (Objective):** To develop an AI-based diagnostic system that accurately classifies common skin diseases to assist dermatologists in Nigeria, enabling faster and more effective diagnosis and treatment. **Problem to be Solved:** Skin disease diagnosis in Nigeria is challenging	Image Dataset,Image Preprocessing Module Pre-trained Deep Learning Model (AlexNet), ,Testing Module,Recognition and Classification,Performance Evaluation Metrics,User Interface

providing a robust automated diagnostic tool that aids dermatologists in decision-making.	due to a shortage of dermatologists and the subjectivity and time required in manual diagnosis. An automated solution is needed to improve diagnosis speed and accuracy, especially for underserved populations.	

The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process

	Process Steps	Advantage	Disadvantage (Limitation)
1	1.Image Collection & Preprocessing: Collect and preprocess 1,800 training and 270 testing images by resizing, cropping, and normalizing to fit the AlexNet model input size. 2.Data Splitting: Split the dataset into 80% for training and 20% for validation during model training. 3.Model Selection & Fine-Tuning: Use the pretrained AlexNet model and fine-tune it to classify nine specific skin disease categories. 4.Model Training: Train the model with the prepared dataset, using the validation set to monitor performance.	High Accuracy: Achieves up to 97.8% recognition accuracy, providing reliable skin disease diagnoses. Faster Diagnosis: Automates the diagnosis process, significantly reducing the time required for dermatologists to analyze skin conditions. Assists Dermatologists: Supports dermatologists in decision-making by providing accurate classification results, enhancing clinical efficiency. Scalable & Accessible: Enables access to diagnostic capabilities in underserved areas	Limited to Predefined Diseases: The system is trained to classify only the nine specific skin diseases, limiting its ability to diagnose other rare or newly emerging skin conditions. Dependence on Image Quality: The accuracy of the system heavily relies on the quality of the input images. Poor resolution, lighting, or distortions in the images can reduce the model's performance. Data Requirement: The model requires a large and diverse dataset for accurate training, which may be difficult to obtain for some skin diseases or in regions with

	5. Testing & Evaluation: Test the model on the separate testing dataset and evaluate performance using metrics like accuracy and rejection rate. 6. Deployment: Deploy the model for real-world use, allowing dermatologists to upload images and receive diagnoses.	with limited access to dermatologists, especially in developing countries like Nigeria. Reduces Human Error: Minimizes subjective errors in manual diagnoses, ensuring consistent and objective results across cases.	limited access to image data. Generalization Issues: The model might struggle to generalize well across different populations or skin tones, especially if the dataset is not diverse enough.

Major Impact Factors in this Work			
Dependent Variable	**Independent Variable**	**Moderating variable**	**Mediating (Intervening) variable**
Skin Disease Classification Outcome	Image Data	Image Quality (Resolution, Lighting)	Pretrained Model (AlexNet) Model Architecture Training Process

Relationship Among The Above 4 Variables in This article
The image data (independent variable) is fed into the AlexNet model (mediating variable) for analysis.The quality of the images (moderating variable) influences how effectively the model processes the data and impacts the accuracy of the skin disease classification (dependent variable).In essence,the image data influences the classification outcome through the mediating role of the pretrained model (AlexNet), with the image quality acting as a moderating factor that can either enhance or impair the final classification result

Input and Output		Feature of This Solution	Contribution & The Value of This Work
Input	**Output**	This AI-based skin disease diagnostic solution offers high accuracy, achieving 97.8% recognition accuracy using a pretrained AlexNet deep learning model fine-tuned for skin disease classification. It covers nine common skin diseases and automates image preprocessing	contribution of this work lies in the development of an AI-driven system for efficient and accurate skin disease diagnosis, specifically targeting the nine most common skin disorders in Nigeria. By utilizing a pretrained AlexNet deep learning model, the system enhances the diagnostic capabilities of
The input to the system consists of images of skin	The output of the system is the predicted-		

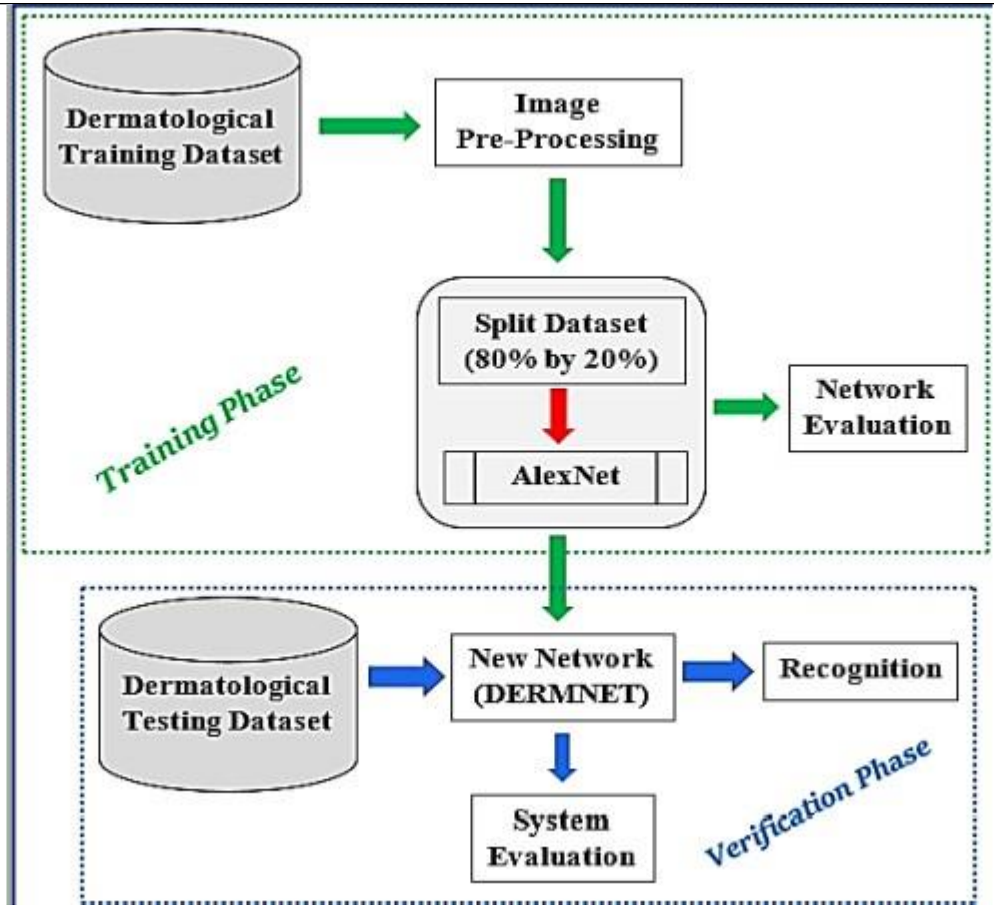
diseases, with a total of 1,800 training images and 270 testing images. These images are collected from various sources and cover nine different types of skin conditions. Before being fed into the system, the images undergo preprocessing steps, which include cropping to focus on the area of interest and resizing to a standardized dimension of 227x227x3 pixels to match the input requirements of the AlexNet model. The dataset is split into training and testing sets to help the model learn and evaluate its performance accurately. The	classification of the skin disease from one of the nine categories, such as acne, eczema, or psoriasis. The system also provides the recognition accuracy, which indicates the percentage of correct predictions made by the model (e.g., 97.8%). Additionally, it calculates the rejection rate, representing the percentage of instances where the system is unable to make a confident prediction (e.g., 2.2%). Finally, the model outputs a confidence score, showing how certain it is about the classification decision, helping to assess the reliability of the prediction.	tasks like cropping and resizing for consistent input. The system provides rapid diagnosis with a low rejection rate of 2.2%, ensuring reliability. It is user-friendly, aiding dermatologists in decision-making without replacing their expertise, and is scalable, allowing for expansion to include more diseases and data over time.	dermatologists, aiding them in making quicker, more reliable decisions. This solution addresses the challenge of limited dermatological resources in regions with few specialists, providing an accessible tool for faster skin disease detection. The work also adds value by improving healthcare accessibility, reducing diagnostic errors, and offering a scalable platform that can be expanded to diagnose more skin conditions in the future.

processed images serve as the key data for the deep learning model to classify the diseases.		

Positive Impact of this Solution in This Project Domain	**Negative Impact of this Solution in This Project Domain**
The positive impact of this solution in the field of dermatology is significant. By leveraging AI and deep learning, the system enhances diagnostic accuracy and speed, enabling quicker identification of skin diseases. This is particularly beneficial in regions with limited access to dermatologists, as it provides an accessible tool for both healthcare professionals and patients. The system reduces the burden on specialists, minimizing diagnostic errors and ensuring more timely treatment, which can ultimately lead to better patient outcomes. Additionally, the scalability of the system means it can be expanded to address a broader range of skin conditions, further improving healthcare accessibility and efficiency.	The negative impact of this solution could include over-reliance on the AI system, potentially diminishing the role of dermatologists in clinical decision- making. While the system is highly accurate, it may not account for all variables, such as rare or complex cases that require expert judgment. Additionally, there could be concerns about data privacy and security, as sensitive patient information is processed and stored digitally. The system's effectiveness is also dependent on the quality and diversity of the training dataset, meaning any biases or gaps in the dataset could lead to inaccurate diagnoses for certain populations or conditions. Finally, the initial cost of implementation and the need for continuous updates to keep the model relevant may present challenges for resource-constrained healthcare settings.

Analyse This Work By Critical Thinking	**The Tools That Assessed this Work**	**What is the Structure of this Paper**
This AI-driven skin disease diagnostic system offers a promising solution to improve healthcare, especially in regions with a shortage of dermatologists. Its high accuracy and scalability can enhance diagnostic speed and consistency. However, its effectiveness depends on the quality of the training data, and its "black-	The tools used to assess this work include the pretrained AlexNet model, which was fine-tuned for skin disease classification, along with image preprocessing techniques like cropping and resizing. A dataset of 2,070 images (1,800 for training and 270 for testing) was used to evaluate the model's accuracy and generalization.	I. Abstract II. Introduction III. Statement of the Problem IV. Empirical Review of Literature V. Proposed method

box" nature may reduce trust among healthcare professionals. There's also a risk of over-relying on the system for complex cases, and privacy concerns regarding patient data must be addressed. While it can be a valuable tool, it should complement, not replace, human expertise in dermatology, with ongoing improvements to ensure broad accessibility and effectiveness.	Performance metrics such as recognition accuracy, rejection rate, and validation accuracy were applied to assess the model's effectiveness, while descriptive statistics were used for further evaluation. The system was tested in a stable environment with specific machine configurations, ensuring reliable performance during the process.	VI. Results VII. Conclusion VIII. References
Diagram/Flowchart		



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<tr><td colspan="3">5</td></tr>
<tr><td>Reference in APA format</td><td colspan="2"></td></tr>
<tr><td>URL of the Reference</td><td>Authors Names and Emails</td><td>Keywords in this Reference</td></tr>
<tr><td>https://doi.org/10.21203/rs.3.rs-2889033/v1</td><td>Minhong Wang,Ewa Kloczko,Alla Altayeb,Michael Farrugia,Girish Gupta,Honghan Wu,Nik Hirani</td><td>Automated Triage,Deep Learning,Artificial Intelligence,Dermatology,Natural Language Processing,Knowledge-Driven Approaches,Clinical Guidelines,Referral Letters,Machine Learning Models,Data Imbalance</td></tr>
<tr><td>The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)</td><td>The Goal (Objective) of this Solution & What is the problem that need to be solved</td><td>What are the components of it?</td></tr>
<tr><td>The current solution in the paper "Towards Automated Dermatology Triage: Deep Learning and Knowledge-Driven Approaches" includes several key components: a Knowledge-Driven Model that incorporates clinical guidelines, a BERT Model for text classification of referral letters, an LSTM (Long Short-Term Memory) model for processing medical concepts, a Transfer Learning Approach utilizing pre-trained models, and Data Augmentation Techniques to handle class</td><td>The goal of the solution in "Towards Automated Dermatology Triage: Deep Learning and Knowledge-Driven Approaches" is to create AI models that can automatically classify General Practitioner (GP) referrals into routine and non- routine categories. The problem being addressed is the time-consuming and costly manual triage process currently used in the NHS, where clinicians must read each referral letter individually. By automating this process, the solution aims to
enhance efficiency, reduce clinician workload, and</td><td>The solution in "Towards Automated Dermatology Triage" comprises a Knowledge-Driven Model with clinical guidelines and custom dictionaries, Deep Learning Models like BERT for text classification and LSTM for medical concept processing, and Transfer Learning to leverage pre-trained models. It uses Data Preprocessing, including random oversampling and augmentation, to address class imbalance, and UMLS for extracting key medical concepts from referral letters.</td></tr>
</table>

imbalance in the dataset.	maintain accuracy in patient categorization.	

The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process

The model in "Towards Automated Dermatology Triage" integrates clinical guidelines with AI, using BERT and LSTM with Data Preprocessing to classify GP referrals as routine or non-routine. This approach improves triage accuracy and efficiency while ensuring interpretability.

	Process Steps	Advantage	Disadvantage (Limitation)
1	Data Preprocessing and Concept Extraction	Data Preprocessing and Concept Extraction in "Towards Automated Dermatology Triage" enhance model performance by addressing class imbalance with methods like random oversampling and data augmentation, improving the training dataset's quality. Concept extraction with UMLS identifies key medical terms in referral letters, leading to a more accurate, interpretable triage process that closely aligns with human clinical decision-making.	The approach in "Towards Automated Dermatology Triage" faces challenges with high computational complexity from deep learning models and attention mechanisms, demanding substantial resources. Limited data, with only 268 referrals, may reduce model generalizability across diverse clinical scenarios. Additionally, the knowledge-driven model, while interpretable, could introduce biases based on the chosen concepts and guidelines, impacting applicability across healthcare settings.
2	Model Development and Evaluation	Model Development and Evaluation in "Towards Automated Dermatology Triage" improve triage accuracy by integrating multiple AI models and systematically comparing them to manual outcomes. This approach helps identify the best-performing model, aligning AI-assisted triage with clinician-level accuracy. Metrics like PR-AUC and ROC-AUC offer quantifiable performance insights, supporting ongoing refinement of the triage system.	Disadvantages of the approach in "Towards Automated Dermatology Triage" include potential overfitting due to a limited dataset of 268 referrals, possibly limiting model generalizability. The use of complex models like BERT and LSTM increases computational costs and processing time, impacting feasibility for real-time use. Bias risks from selected concepts and training data could affect applicability across healthcare settings, and limited model interpretability may reduce clinician trust.

Major Impact Factors in this Work

The study "Towards Automated Dermatology Triage" leverages AI to automate GP referral triage, reducing time and costs, while knowledge-driven models improve interpretability and accuracy by incorporating clinical guidelines. Addressing data imbalance further enhances model performance for reliable triage outcomes.

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
The primary dependent variable is the classification outcome of GP referrals into routine or non-routine categories, which reflects the effectiveness of the triage process.	These include the different AI models used for triaging referrals (e.g., knowledge-driven model, BERT model, LSTM model) and preprocessing techniques (e.g., random oversampling, data augmentation).	Factors such as the complexity of referral letters, clinician experience, and the quality of extracted medical concepts may influence the relationship between the independent variables (AI models) and the dependent variable (triage outcomes).	The performance metrics used to evaluate model effectiveness (e.g., PR-AUC, ROC-AUC) can act as mediators by demonstrating how well the AI models translate into accurate triage classifications based on their design and training.

Relationship Among The Above 4 Variables in This article

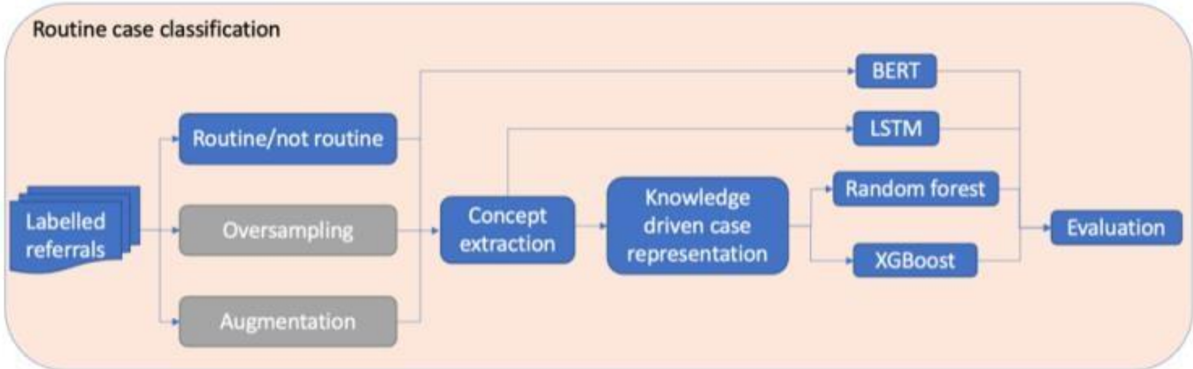
Input and Output	Feature of This Solution	Contribution & The Value of This Work
Input: The primary input consists of GP referral letters, which are processed to extract relevant medical concepts using the Unified Medical Language System (UMLS). These letters are then categorized as **Output:** The output of the model is a binary classification of each referral letter into two categories: **routine** and **non-routine**. This classification aims to assist in triaging decisions, allowing for more efficient allocation of clinical resources.	The work "Towards Automated Dermatology Triage" integrates AI to streamline GP referral triage, significantly reducing time and costs. Knowledge-driven models enhance interpretability and accuracy by incorporating clinical guidelines and medical concepts. Addressing data imbalance with techniques like random oversampling further improves model performance. Overall, this approach aims to enhance efficiency while upholding high patient care standards. 4o	The contribution of "Towards Automated Dermatology Triage" lies in developing AI models that classify GP referrals into routine and non-routine categories, addressing time and cost challenges in manual triage. The knowledge-driven model incorporates clinical guidelines, achieving clinician-level performance and improving dermatology resource allocation. It also demonstrates AI's potential to streamline workflows, reduce patient waiting times, and enhance healthcare quality.

either routine or non-routine referrals based on the information contained within them.		

Positive Impact of this Solution in This Project Domain	Negative Impact of this Solution in This Project Domain
The solution in "Towards Automated Dermatology Triage" significantly impacts healthcare by automating GP referral triage, reducing time and costs while improving accuracy. AI models ensure urgent cases are prioritized, and the approach streamlines workflows, addressing indirect employment and opportunity costs in the NHS. This contributes to efficient healthcare delivery and enhanced patient care.	The solution in "Towards Automated Dermatology Triage" faces challenges like over-reliance on AI, potentially diminishing clinician engagement and judgment in complex cases. Limited training data may lead to overfitting and reduced generalizability. The complexity of deep learning models increases computational costs and processing time, affecting real-time feasibility. Additionally, the lack of interpretability could hinder clinician trust and slow adoption in clinical settings.

Analyse This Work By Critical Thinking	The Tools That Assessed this Work	What is the Structure of this Paper
"Towards Automated Dermatology Triage" presents a significant advancement by integrating AI with clinical guidelines, improving triage efficiency. The study's robust evaluation using multiple AI models and data preprocessing techniques addresses class imbalance effectively. However, the limited dataset and model complexity raise concerns about generalizability and interpretability. Potential biases in the	AI Models (Knowledge-driven model, BERT, LSTM) Data Preprocessing Techniques Performance Metrics (PR-AUC, ROC-AUC) Unified Medical Language System (UMLS) SemEHR Tool	Abstract Introduction Materials and Methods Results Discussion Conclusion References

knowledge-driven approach could affect outcomes. Future research should focus on expanding datasets, improving transparency, and ensuring seamless integration into clinical workflows for better patient care.		
Diagram/Flowchart		



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<table>
<tr><th colspan="3">6</th></tr>
<tr><td>Reference in APA format</td><td colspan="2"></td></tr>
<tr><td>URL of the Reference</td><td>Authors Names and Emails</td><td>Keywords in this Reference</td></tr>
<tr><td>https://www.researchgate.net/publication/382355999_Revolutionizing_Skin_Cancer_Triage_The_Role_of_Patient-Initiated_Teledermoscopy_in_Remote_Diagnosis</td><td>Emilie A. Foltz,Joanna Ludzik,Sancy Leachman,Elizabeth Stoos,Teri Greiling,Noelle Teske,Lara Clayton,Alyssa L. Becker,Alexander Witkowski</td><td>teledermatology; dermoscopy; teledermoscopy; melanoma triage; skin cancer triage; dermatology access; telehealth; telemedicine; early detection</td></tr>
<tr><td>The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)</td><td>The Goal (Objective) of this Solution & What is the problem that need to be solved</td><td>What are the components of it?</td></tr>
<tr><td>Patient-Initiated Teledermoscopy enhances skin cancer triage by allowing patients to capture high-quality images of skin lesions with smartphone dermatoscope attachments for remote dermatologist evaluation. This method reduces in-person visits, with a 53% decrease in follow-up visits, and improves access to care, addressing dermatology shortages and long wait times. It empowers patients to monitor skin health and aids in earlier detection of malignant lesions.</td><td>Patient-Initiated Teledermoscopy addresses critical barriers in dermatological care by enabling patients to capture and submit images of skin lesions remotely, improving access to care amid a dermatologist shortage. It reduces in-person visits for benign lesions, prioritizing consultations for potentially malignant ones. The solution also tackles patient education challenges, empowering individuals to conduct self-skin examinations and aiding early detection of skin cancer, particularly amid increased demand during the COVID-19 pandemic.</td><td>Smartphone Dermatoscope Attachment, Mobile Application or Secure Portal, Training and Educational Resources, Remote Evaluation by Dermatologists, Feedback Mechanism, Data Collection and Analysis, Loaner Program for Devices.</td></tr>
<tr><th colspan="3">The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process</th></tr>
<tr><td colspan="3">The study demonstrates that patient-initiated teledermoscopy, incorporating dermoscopic images, significantly reduces in-person consultations, enhancing access to dermatological care. This approach shows promise in improving early detection and management of skin cancer while addressing physician shortages.</td></tr>
</table>

	Process Steps	Advantage	Disadvantage (Limitation)

1	Image Capture and Submission	Patients actively engage in their healthcare by capturing images of their skin lesions, fostering greater awareness of their skin health. The ability to take images at home provides convenience, especially for those in remote areas or with mobility issues. Smartphone dermatoscopes deliver high-quality images that enhance diagnostic accuracy by revealing features not visible to the naked eye.	Patients may encounter technical challenges in using the smartphone dermatoscope effectively, potentially resulting in poor-quality images that hinder accurate evaluations. The variability in image quality can significantly impact diagnostic outcomes, as it depends on the patient's skill and understanding of device usage. Additionally, limited training for some patients on recognizing concerning lesions or using the technology may contribute to missed or delayed diagnoses.
2	Remote Evaluation	Dermatologists can remotely assess images, overcoming geographical and scheduling limitations, ensuring expert evaluation. The remote triage process allows for prioritizing urgent cases while efficiently managing those that can be monitored remotely, optimizing resource allocation. Additionally, reducing unnecessary in-person visits for benign lesions alleviates the burden on healthcare facilities, allowing them to focus on patients with more serious conditions.	Remote evaluations may lack the comprehensive context of an in-person examination, increasing the risk of misdiagnosis or missed malignancies. The accuracy of these assessments depends heavily on the quality of the submitted images, with poor-quality images compromising diagnostic reliability. Additionally, the limited interaction in remote evaluations reduces opportunities for direct communication, potentially affecting the understanding and trust between patients and healthcare providers.
3	Feedback and Follow-Up	Timely communication provides patients with prompt feedback on their lesion evaluations, reducing anxiety and enabling timely follow-up actions. Personalized care recommendations enhance patient understanding of their skin	Limited personal interaction in electronic feedback may not provide the same reassurance or clarity as face-to-face consultations, which some patients prefer. There is also the potential for patients to misinterpret feedback or

		conditions and encourage adherence to follow-up care. Additionally, continuous data collection through feedback helps improve teledermoscopy practices by informing future decisions and enhancing patient outcomes.	recommendations due to a lack of medical knowledge, causing confusion about their skin health. Additionally, coordinating follow-up care can be challenging when patients are not physically present, leading to delays in necessary treatments or interventions.

Major Impact Factors in this Work
The Patient-Initiated Teledermoscopy study improves access to dermatological care, reduces unnecessary in-person visits, and enhances patient engagement. It also offers cost savings and supports the integration of telemedicine into dermatology, laying the groundwork for future research.

Dependent Variable	**Independent Variable**	**Moderating variable**	**Mediating (Intervening) variable**
Number of In-Person Consultations, Patient Satisfaction, Diagnostic Accuracy	Image Type Submitted, Patient Education Level, Demographic Factors	Quality of Submitted Images, Patient Engagement	Access to Technology, Healthcare System Factors

Relationship Among The Above 4 Variables in This article

Input and Output	**Feature of This Solution**	**Contribution in This Work**
<table><tr><th></th><th></th></tr><tr><td>Patient Enrollment, Device Loan, Image Capture, Image Submission</td><td>Remote Evaluation Results, Reduction in In-Person Visits, Patient Feedback, Data Collection for Analysis images</td></tr></table>	The Patient-Initiated Teledermoscopy solution enhances skin cancer triage through features like smartphone dermatoscope attachments for high-quality images, remote image submission via a secure portal, and expert dermatologist evaluations. It reduces unnecessary in-person consultations by 53%, improving access to care. Comprehensive patient training and a feedback mechanism foster engagement and satisfaction. The system collects data for ongoing analysis and is cost-effective by reducing travel and office visit costs. These features make teledermoscopy	The Patient-Initiated Teledermoscopy study demonstrates a 53% reduction in in-person consultations, enhancing access to care, particularly in underserved areas. It empowers patients to actively monitor their skin health and contributes to the integration of telemedicine in dermatology. The study highlights cost savings by reducing travel and office visit expenses. Data-driven insights from the research can inform future teledermoscopy improvements. This work lays the foundation for future research in teledermatology, addressing healthcare challenges post-COVID-19.

	a promising strategy for better skin cancer detection and dermatological access.	

Positive Impact of this Solution in This Project Domain	Negative Impact of this Solution in This Project Domain
The Patient-Initiated Teledermoscopy solution improves dermatological care by enhancing access to services, especially in remote areas. It reduces unnecessary in-person visits, improving healthcare efficiency. The system empowers patients to monitor their skin health, fostering early detection. It offers cost savings by minimizing travel and office visit expenses. Additionally, it streamlines triage processes, allowing dermatologists to prioritize urgent cases.	Patient-Initiated Teledermoscopy may suffer from inadequate patient education, leading to missed or delayed diagnoses. Poor image quality can hinder accurate remote evaluations, risking misdiagnoses. Over-reliance on technology may reduce traditional clinical skills among dermatologists. The lack of in-person interactions can increase patient anxiety and confusion. Additionally, accessibility issues and regulatory concerns regarding privacy and security may limit the system's effectiveness.

Analyse This Work By Critical Thinking	The Tools That Assessed this Work	What is the Structure of this Paper
The Patient-Initiated Teledermoscopy offers innovative technology for skin cancer detection, reducing the need for in-person visits and empowering patients to monitor their skin health. However, challenges such as variable image quality, potential misdiagnosis, and patient education gaps remain. The approach has the potential to transform healthcare delivery and improve access to dermatological care. Future research should focus on enhancing technology usability and patient education. Overall, the solution shows promise in advancing dermatology by improving early diagnosis and reducing healthcare burdens.	Smartphone Dermatoscope Attachment, Secure Electronic Medical Record System, Clinical Algorithms for Evaluation, Statistical Analysis Tools, Opportunity Cost Estimation Methodology, Qualitative Metrics Collection, Summary of Assessment Approach	Title, Authors and Affiliations, Abstract, Keywords, Introduction, Materials and Methods, Study Design, Participants, Image Submission Process, Outcome Measures, Results, Discussion, Conclusion, Acknowledgments, References, Figures and Tables

Diagram/Flowchart

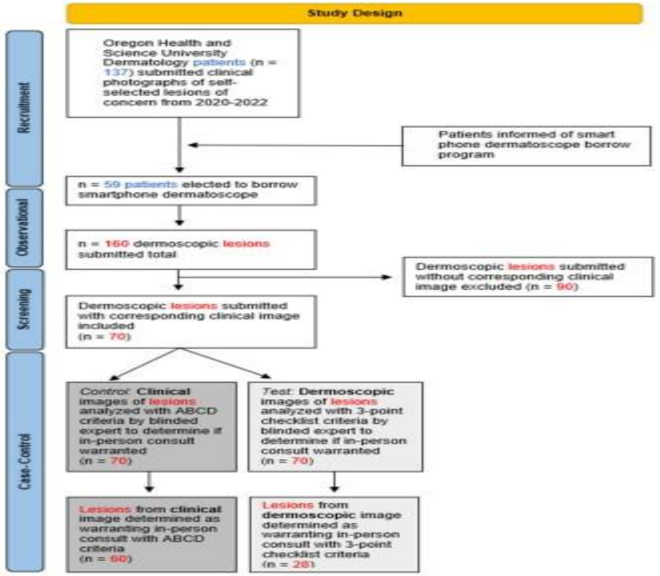

Figure 1. Overview of study design and primary outcomes.

End of paper 6

<table>
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<tr><td colspan="3">7</td></tr>
<tr><td>Reference in APA format</td><td colspan="2"></td></tr>
<tr><td>URL of the Reference</td><td>Authors Names and Emails</td><td>Keywords in this Reference</td></tr>
<tr><td>https://www.nature.com/articles/nature21056</td><td>Andre Esteva, Brett Kuprel, Roberto A. Novoa, Justin Ko, Susan M. Swetter, Helen M. Blau, Sebastian Thrun</td><td>Skin cancer, deep learning, convolutional neural network, dermatologist-level classification, melanoma, non-melanoma skin cancer.</td></tr>
<tr><td>The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)</td><td>The Goal (Objective) of this Solution & What is the problem that need to be solved</td><td>What are the components of it?</td></tr>
<tr><td>Convolutional Neural Network (CNN) model for skin cancer classification.</td><td>Objective: To develop an AI model that can classify skin cancer with accuracy comparable to dermatologists.</td><td>Large-scale image dataset of skin lesions,Convolutional Neural Network (CNN) architecture for image classification,Model training and validation processes</td></tr>
</table>

	Problem: Early and accurate diagnosis of skin cancer is critical but limited by access to skilled dermatologists. This solution aims to bridge that gap with an automated, high-precision classification tool.	

The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process

The model was trained on a large dataset of labeled skin lesion images, using CNN to classify images as benign or malignant.

	Process Steps	Advantage	Disadvantage (Limitation)
1	Image Dataset Collection	Enables robust model training and high accuracy	Requires significant time and resources for dataset curation
2	CNN Model Training	Provides high classification accuracy	High computational cost and need for high-quality data
3	Validation with Dermatologists	Ensures real-world relevance and accuracy verification	Limited to dataset constraints and might miss rare cases

Major Impact Factors in this Work

The model leverages a large, diverse dataset of skin lesions to achieve high accuracy comparable to dermatologists, with potential for deployment in remote or underserved areas.

Skin cancer classification outcome	Image features extracted from skin lesions.	Image quality and variability in lesion presentation.	CNN layers and architecture that process image features for classification.

Relationship Among The Above 4 Variables in This article
Image quality affects feature extraction, which the CNN architecture then processes, leading to a skin cancer classification outcome. The CNN layers act as a mediator between the input image features and the final classification accuracy.

Input and Output	**Feature of This Solution**	**Contribution & The Value of This Work**
Input: skin lesion images **Output**: Classification of lesion type	Provides dermatologist-level classification of skin lesions, making it accessible and potentially deployable as an early diagnostic tool	This work is significant for healthcare by offering a scalable and high-accuracy tool for skin cancer screening, especially beneficial in areas lacking dermatologists.

Positive Impact of this Solution in This Project Domain	Negative Impact of this Solution in This Project Domain
Increases accessibility to early skin cancer detection, reducing the risk of late-stage diagnosis and associated mortality.	Potential for misdiagnosis if image quality is poor or the model is applied without appropriate caution or oversight.

Analyse This Work By Critical Thinking	The Tools That Assessed this Work	What is the Structure of this Paper
The article presents a CNN model that demonstrates high accuracy in skin cancer classification, but it highlights challenges like model dependency on high-quality datasets and potential limitations when deployed in real-world, varied environments.	CNN Model: For image classification Cross-validation: For model performance evaluation .	i)Abstract ii). Introduction iii). Methods iv). Results v)Discussion vi)I. Conclusion

Diagram/Flowchart


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<tr><th colspan="3">8</th></tr>
<tr><th>Reference in APA format</th><td colspan="2"></td></tr>
<tr><th>URL of the Reference</th><th>Authors Names and Emails</th><th>Keywords in this Reference</th></tr>
<tr><td>https://www.sciencedirect.com/science/article/pii/S0010482523008788?via%3Dihub</td><td>Nan Luo, Xiaojing Zhong, Luxin Su, Zilin Cheng, Wenyi Ma, and Pingsheng Hao.</td><td>Dermatology, AI-assisted diagnosis, Machine learning, Multimodal, Pre-training, Federated learning</td></tr>
<tr><th>The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)</th><th>The Goal (Objective) of this Solution & What is the problem that need to be solved</th><th>What are the components of it?</th></tr>
<tr><td>The current solution proposed in the reference is Large-scale pre-training multimodal models</td><td>To improve diagnostic accuracy in dermatology by combining multiple data types (e.g., images and text) to overcome limitations of unimodal AI models.</td><td>Multimodal neural networks

Pre-training with large datasets

Federated learning for data privacy</td></tr>
<tr><th colspan="3">The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process</th></tr>
<tr><td colspan="3"></td></tr>
</table>

	Process Steps	Advantage	Disadvantage (Limitation)
1	Data Pre-Processing	Allows AI to learn from a vast, unlabeled dataset for general knowledge	High Computational demand for processing and fine-tuning

2	Federated Learning	Ensures patient privacy in data sharing and model training	Increased complexity in maintaining model accuracy across different sources
3	Multimodal Fusion	Enhances diagnostic capability by integrating image, text, and other data	Complexity in parameter tuning and increased risk of overfitting

Major Impact Factors in this Work

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
Diagnostic accuracy and specificity in dermatology.	Type and quality of input data, including text, images, and patient history.	Privacy regulations affecting data sharing methods.	Model architecture, including multimodal integration and pre-training mechanisms.

Relationship Among The Above 4 Variables in This article
The diagnostic accuracy (dependent variable) depends on the data quality (independent variable) while being moderated by privacy regulations. The multimodal model's architecture mediates the integration of data, directly impacting accuracy.

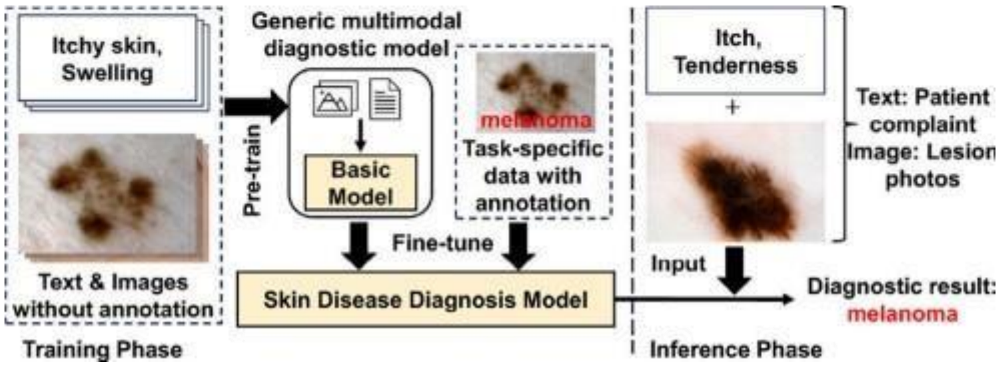
Input and Output	Feature of This Solution	Contribution & The Value of This Work
Input: MultimodalPatient data **Output**: Accurate dermatology diagnosis	The solution combines diverse data types and applies federated learning to ensure privacy, enhancing diagnostic accuracy and robustness.	This work enables high-precision diagnosis by merging multimodal data while preserving privacy, advancing dermatology diagnostics.

Input	Output
MultimodalPatient data	Accurate dermatology diagnosis

Positive Impact of this Solution in This Project Domain	Negative Impact of this Solution in This Project Domain
Enhanced diagnostic precision and support for remote/self-diagnosis, promoting data security through federated learning.	High computational and resource demands for multimodal model training, with a need for extensive labeled data.

Analyse This Work By Critical Thinking	The Tools That Assessed this Work	What is the Structure of this Paper
This approach effectively addresses limitations of unimodal AI by integrating multiple data types, though it demands substantial computational power and carefully managed privacy safeguards.	Federated learning for secure data handling Transformer-based models for handling diverse data types	1. Abstract 2. Introduction 3. Computer-aided diagnosis 4. Text-based AI diagnostics 5. Image-based AI diagnostics 6. Multimodal models and pre-training 7. Future directions 8. Conclusion

Diagram/Flowchart



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9		
Reference in APA format		
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
https://doi.org/10.21203/rs.3.rs-2106798/v1	Junwei Lv, Daojun Zhang	Skin disease diagnosis, AI, dual-channel model, U-Net, ResNet, text-image integration, dermatology.
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)	**The Goal (Objective) of this Solution & What is the problem that need to be solved**	**What are the components of it?**
Dual-channel Image and Extracted Text (DIET) Model	**Goal**: Improve the accuracy and accessibility of skin disease diagnosis by integrating image data with text data from medical records. **Problem**: The shortage of dermatologists and unequal access to diagnostic resources in certain regions limits effective skin disease diagnosis, often requiring both imaging and comprehensive patient information for accuracy.	Dual-channel Model U-Net Detection Logistic Regression
The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process		

	Process Steps	Advantage	Disadvantage (Limitation)

1	Image Preprocessing (U-Net) and Feature Integration	**Accurate localization of lesions and Improved diagnostic performance**	May misidentify small or unclear lesions and Increases overall model complexity and training time
2	Dual-channel ResNet Processing and Text Extraction (One-hot)	Uses both local and global image information and Adds clinical context unavailable in images alone	High computational cost and Limited by text data accuracy

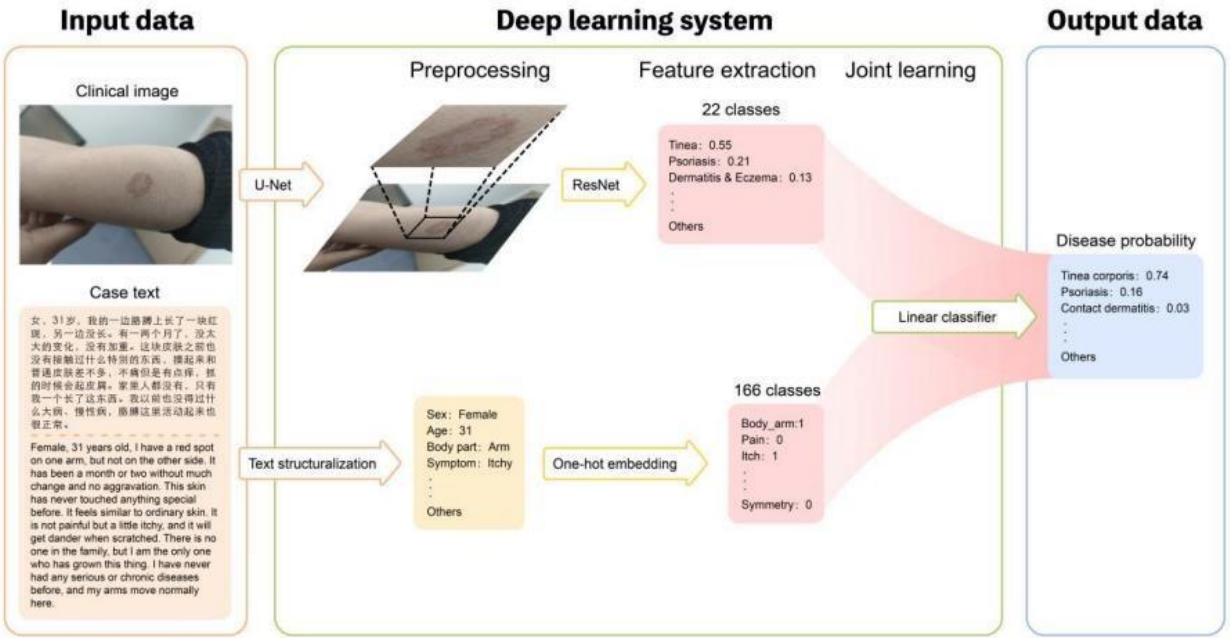
Major Impact Factors in this Work
Integration of multi-modal data (image and text) and Enhanced diagnostic accuracy through dual-channel processing , with Accessibility for primary-level dermatologists in underserved areas.

Dependent Variable	**Independent Variable**	**Moderating variable**	**Mediating (Intervening) variable**
Diagnostic accuracy for 31 skin diseases	Skin images and patient medical records	Skin disease severity, type, and environmental lighting in images	Dual-channel feature integration (ResNet + One-hot)

Relationship Among The Above 4 Variables in This article

Input and Output		**Feature of This Solution**	**Contribution & The Value of This Work**
		Dual-channel processing of skin images and medical records and Disease classification with diagnostic probabilities, enhancing diagnostic reliability in dermatology.	This work proposes a novel AI diagnostic model (DIET-AI) that outperforms junior doctors and matches the diagnostic accuracy of senior dermatologists. This model provides a significant step toward equitable access to dermatological diagnosis in resource-constrained settings.
Skin images and electronic health records	Predicted skin disease with associated		

<table>
<tr><td>(text data) | diagnostic probabilities</td><td colspan="2"></td><td></td></tr>
<tr><td colspan="2">Positive Impact of this Solution in This Project Domain</td><td colspan="2">Negative Impact of this Solution in This Project Domain</td></tr>
<tr><td colspan="2">Increases diagnostic accessibility and accuracy in dermatology, especially for common skin conditions in Asia.</td><td colspan="2">High computational demands and reliance on quality data, which may limit application in low-resource environments.</td></tr>
<tr><td>Analyse This Work By Critical Thinking</td><td colspan="2">The Tools That Assessed this Work</td><td>What is the Structure of this Paper</td></tr>
<tr><td>This model integrates multi-modal data to improve diagnostic accuracy, addressing limitations in skin disease diagnosis by utilizing both image and text, yet faces challenges with high data processing needs.</td><td colspan="2">U-Net: For lesion detection and segmentation
ResNet: Dual-channel feature extraction
Logistic Regression: For final diagnostic prediction based on integrated features.</td><td>Abstract
I. Abstarct
II. Introduction
III. Methods(algorithm ,data collection)
IV. Results
V. Discussion
VI. Conclusion</td></tr>
<tr><td colspan="4">Diagram/Flowchart</td></tr>
</table>



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<tr><th>URL of the Reference</th><th>Authors Names and Emails</th><th>Keywords in this Reference</th></tr>
<tr><td>https://doi.org/10.7759/cureus.59906</td><td>Samantha Tyler, Robin J. Jacobs , Tyler, S., Olis, M., Aust, N., Patel, L., Simon</td><td>Emergency department triage, artificial intelligence, machine learning, predictive analytics, healthcare workflow, clinical decision support.</td></tr>
<tr><th>The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)</th><th>The Goal (Objective) of this Solution & What is the problem that need to be solved</th><th>What are the components of it?</th></tr>
<tr><td>AI-based triage models using ML algorithms like XGBoost, Random Forest, and LASSO regression.</td><td>Goal: To enhance accuracy and efficiency in triaging within Emergency Departments (EDs) by using AI to predict patient outcomes and prioritize care.
Problem: Increasing patient volumes, ED overcrowding, and variation in traditional triage methods have limited EDs' ability to effectively manage critical cases.</td><td>Data Collection: Use of medical databases like EMBASE, MEDLINE, and Web of Science.
AI Model Testing: Algorithms such as XGBoost, LASSO regression, and Neural Networks.
Outcome Comparison: Compared AI-based predictions to traditional triage.</td></tr>
<tr><th colspan="3">The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process</th></tr>
<tr><td colspan="3">The "Deep Multi-view Breast Cancer Detection" system uses deep transfer learning with VGG16 to classify breast thermal images as normal or abnormal, achieving a testing accuracy of 99% by integrating multi-view thermal data.</td></tr>
</table>

	Process Steps	Advantage	Disadvantage (Limitation)
1	Data Collection	Broad search across databases ensures diversity	Limited by criteria specific to U.S. journal scope
2	AI Model Training and Testing	Enhances the model's ability to identify abnormalities by utilizing richer data inputs.	Increased complexity in data handling and potential for overfitting if not managed properly.
3	Comparative Analysis	Shows AI outperforms traditional triage	Potential over-reliance on data accuracy

Major Impact Factors in this Work

Improved triage accuracy through ML algorithms

Enhanced resource allocation in ED settings

Reduced under-triaging and mistriage rates

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
Patient outcomes (admissions, interventions)	Patient demographics, triage data, health metrics	Severity of the presenting condition, ED patient load	Algorithm type and model accuracy

Input and Output	Relationship Among Variables in This Article: AI triage models enhance the accuracy of emergency care, with the condition's severity affecting predictions and resource allocation outcomes.	Contribution in This Work
(see Input/Output table below)	**Negative Impact of this Solution in This Project Domain**	Provides a systematic overview of AI's potential in ED triage, emphasizing AI's ability to reduce error rates in patient prioritization, optimize resource use, and potentially alleviate ED overcrowding.

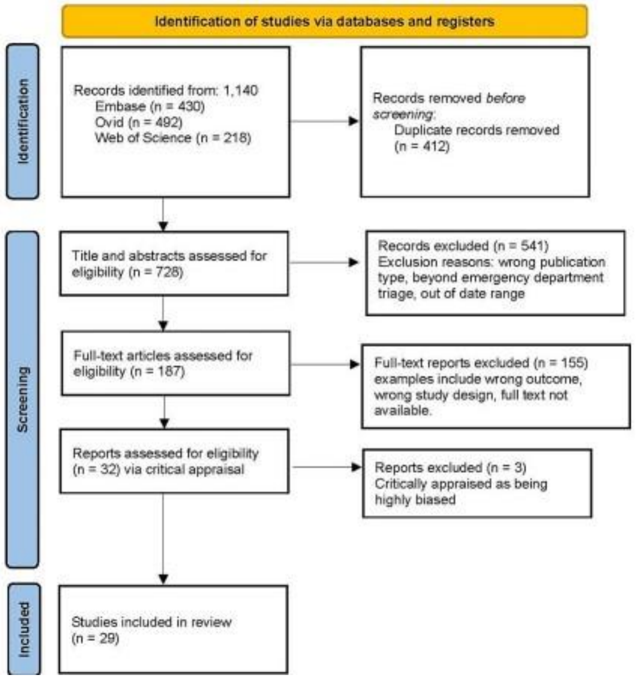
Input	Output
Patient demographics, historical health records, clinical symptoms	Predicted triage level, hospitalization likelihood, urgency assessment

Positive Impact of this Solution in This Project Domain	
Significant improvement in triage decision accuracy and reduction in patient wait times in EDs.	**The Tools That Assessed this Work:** • **XGBoost and Random Forest**: Enhanced discrimination in triage predictions • **LASSO Regression**: For predicting critical care needs

Analyse This Work By Critical Thinking	Feature of this solution	What is the Structure of this Paper
his scoping review consolidates AI-driven solutions for ED triage, showing AI's potential to outperform conventional triage methods. The work highlights	**Input**: Multivariate data, including patient history and symptoms.	1. Abstract 2. Introduction

advancements in ML models but notes high demands on data and computational resources, which could be barriers in under-resourced EDs.	**Output**: Triage assessments with high predictive accuracy, helping clinicians prioritize effectively.	3. Literature Review 4. Methodology 5. Results and Discussion 6. Conclusion

Diagram/Flowchart



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11		
Reference in APA format		
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
https://doi.org/10.1002/ski2.83	Yun Liu; Huang, S. J., Liu, Y., Kanada, K., Corrado, G. S., Webster, D. R., Peng, L., & Bui, P. (2022).	Machine learning, triaging, teledermatology, clinical operations, healthcare prioritization, AI for dermatology.
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)	**The Goal (Objective) of this Solution & What is the problem that need to be solved**	**What are the components of it?**
The ML-based **Deep Learning System (DLS)** for teledermatology prioritizes patient cases by urgency, predicting which cases need immediate review versus those requiring no intervention, thus optimizing dermatologist workflows.	The system aims to address long wait times in dermatology by sorting patient cases by urgency. This reduces the workload on dermatologists by triaging cases needing rapid attention and deferring non-urgent ones.	**Deep Learning Model**: Provides differential diagnoses. **Urgency Mapping**: Assigns cases into five triage categories (e.g., immediate intervention, no need for a doctor). **Automated Triage Ordering**: Reorders cases in review batches to prioritize urgent cases.

The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process

	Process Steps	Advantage	Disadvantage (Limitation)
1	Data Mapping to Urgency Levels and Review Batch Ordering	Accurate prioritization of cases and Efficient prioritization of urgent cases	Requires clinical expertise for accurate mapping and May need adaptation for different clinic needs.
2	Case Triaging and Follow-up Recommendations	Reduces unnecessary wait times for urgent care	Limited by model's diagnostic accuracy

Major Impact Factors in this Work
• **improvement in Wait Times**: Reduces waiting for urgent cases. • **Operational Efficiency**: Streamlines workflow for dermatologists. • **Adaptability**: Can be integrated into various telehealth platforms for scalable triaging. **Variables:**

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
Average wait time for cases	Urgency of patient cases	Patient demographics	Machine learning triage model.

Relationship Among The Above 4 Variables in This article

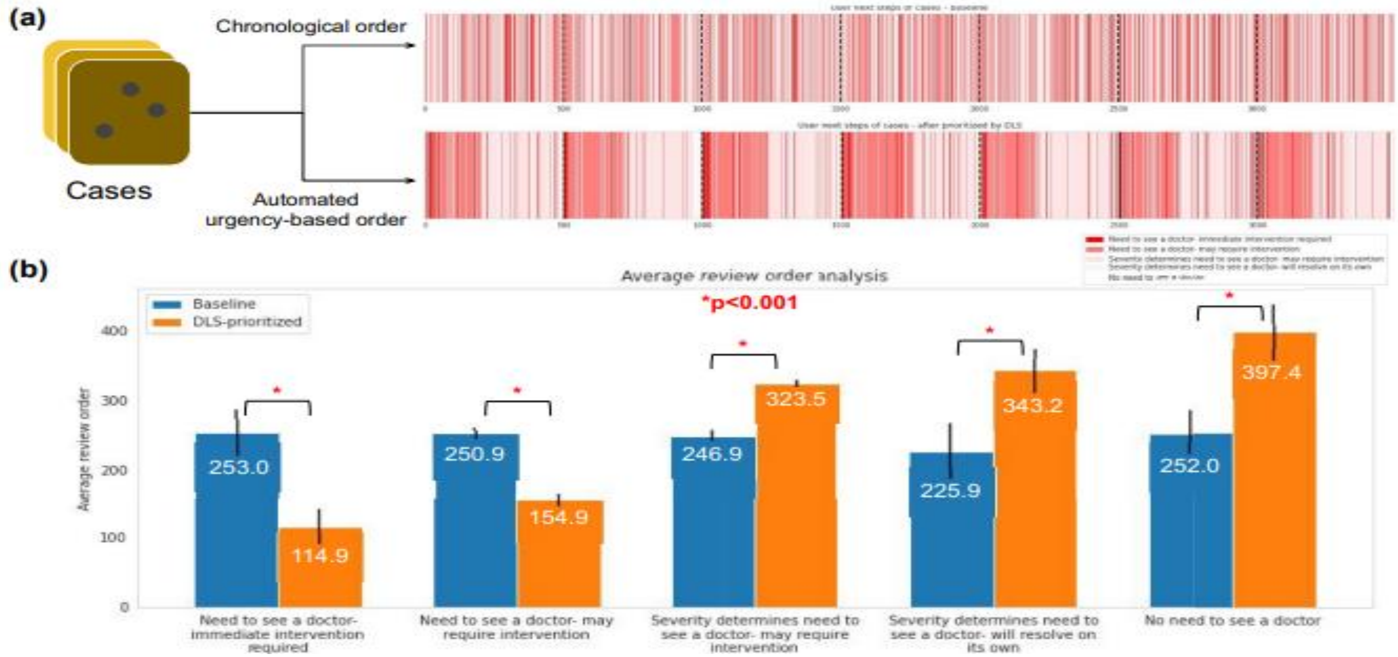
Input and Output		Feature of This Solution	Contribution & The Value of This Work
Input	Output	The features of the DeepSkin solution include the integration of the HAM10000 dataset for diverse skin lesion representation, the application of Convolutional Neural Networks (CNNs) like DenseNet169 and ResNet50 for robust feature extraction, and advanced pre-processing techniques such as the Dull Razor method for noise reduction, which	This ML-based triaging system offers a novel approach to optimizing clinical workflows by efficiently prioritizing urgent cases. It enhances patient care through quicker access to needed treatment and supports teledermatology by reducing dermatologist workloads.
The input for the DeepSkin model consists of dermatoscopic images from the	The output of the DeepSkin model includes the predicted classifications of		

	collectively enhance the model's accuracy in skin cancer classification.	

Positive Impact of this Solution in This Project Domain	Negative Impact of this Solution in This Project Domain
Improves access to dermatologic care, especially in areas with limited healthcare resources, and significantly reduces wait times for urgent cases.	Over-reliance on ML predictions could lead to errors, especially if algorithms are not robust across diverse populations or if model accuracy falls short.

Analyse This Work By Critical Thinking	The Tools That Assessed this Work	What is the Structure of this Paper

This ML model introduces an innovative prioritization method for teledermatology, significantly improving clinical operations by automating urgent case identification. Future improvements could include direct training to predict case urgency and customization for different healthcare practices. Further testing in diverse clinical settings is suggested to enhance its robustness and adaptability.	Convolutional Neural Networks (CNNs): Used for effective feature extraction and classification of skin lesions. Transfer Learning: Implemented with models like DenseNet169 and ResNet50 for improved performance. Data Pre-processing Techniques: Such as the Dull Razor method for noise removal to enhance image quality. .	i)Abstract v). Introduction vi). Literature Review vii).Methodology vii) Results and Discussion viii) I. Conclusion
Diagram/Flowchart		



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12		
Reference in APA format		
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
https://doi.org/10.1186/s12913-024-10663-3	Bipin Adhikari (bipin.adhikari@ox.ac.uk), Debashish Das (Debashish.Das@finddx.org), Bajracharya, M., Aryal, N., Rajbhandari.	Emergency department, Triage, Low-resource healthcare, Patient journey, Nepal, Febrile patients, Healthcare delivery.
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)	**The Goal (Objective) of this Solution & What is the problem that need to be solved**	**What are the components of it?**
WHO Triage Guidelines Adaptation for Low-Resource Setting	**Goal**: Improve triage and emergency care practices in low-resource settings to better serve febrile patients and optimize healthcare worker efficiency. **Problem**: Tertiary hospital EDs in Nepal face constraints in space, resources, and staff training, impacting the effective triage of critical cases.	**Guideline Adherence**: Adopts WHO triage guidelines tailored to resource limitations. **Data Collection**: Observations and in-depth interviews with ED staff and patients. **Process Evaluation**: Identifies challenges in hygiene, recordkeeping, and patient wait times.

The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process		

	Process Steps	Advantage	Disadvantage (Limitation)
1	WHO-based Triage Categories and Observational Studies	Structured response to critical patients and Real-life insights into ED challenges	Inconsistent training among healthcare workers and Limited to single hospital setting
2	Patient Interviews	Highlights patient perceptions and areas for improvement	Possible recall bias

Major Impact Factors in this Work
1. Improved understanding of triage needs in low-resource hospitals. 2. Recommendations for training, digitalization, and resource allocation in EDs. 3. Emphasis on patient satisfaction and healthcare worker motivation.

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
Efficiency and satisfaction of ED triage outcomes	Patient flow, healthcare worker training, equipment availability	Time of day, patient volume, and ED resource constraints	Adherence to WHO triage guidelines, healthcare worker perception

Relationship Among The Above 4 Variables in This article

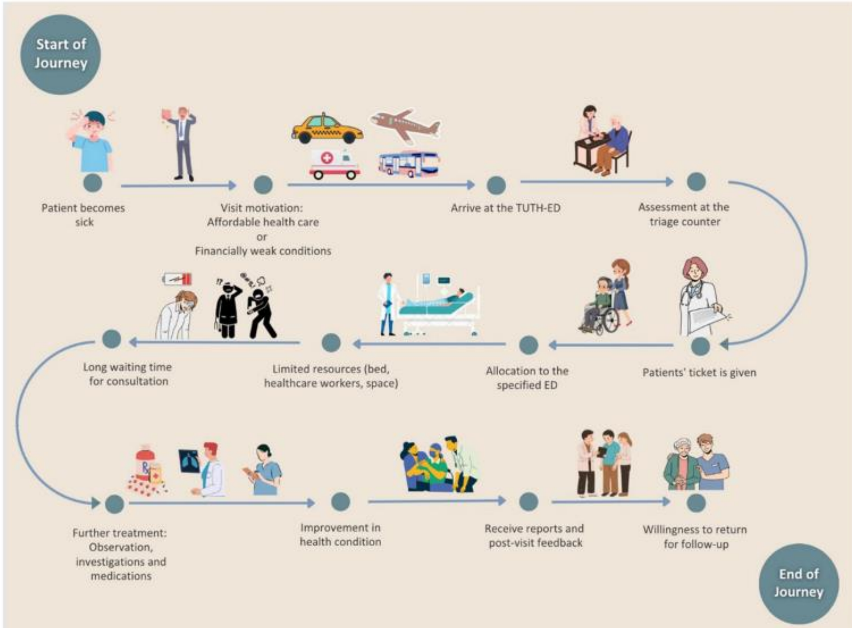
Input and Output	Feature of This Solution	Contribution & The Value of This Work
Input / Output	• **Input**: Patient and staff observations, interviews. • **Output**: Practical recommendations for enhanced ED triage practices.	This study offers an evidence-based evaluation of ED triage in Nepal, providing valuable insights into challenges and actionable recommendations for better resource allocation, workflow efficiency, and patient outcomes.

: Observational and interview data from ED staff and patients.	Recommendations for improving triage efficiency, training, and resource management.		

Positive Impact of this Solution in This Project Domain	Negative Impact of this Solution in This Project Domain
Raises awareness of resource challenges in EDs. And Suggests practical improvements that can enhance patient care and worker satisfaction in low-resource settings.	Dependence on subjective data may limit the generalizability. And Resource recommendations may be challenging to implement in highly constrained settings.

Analyse This Work By Critical Thinking	The Tools That Assessed this Work	What is the Structure of this Paper

This study thoroughly examines ED triage in a challenging environment, highlighting systemic issues in resource management and staff training. However, reliance on qualitative data limits objective measures, underscoring the need for broader validation across other hospitals.	• **Interpretative Phenomenological Analysis (IPA)**: Thematic analysis of interview data. • **WHO Triage Framework**: Structured approach for triage in resource-constrained EDs.	i)Abstract viii). Introduction ix). Literature Review x). Methodology ix) Results and Discussion x) I. Conclusion
Diagram/Flowchart		



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<table>
<tr><th colspan="3">13</th></tr>
<tr><th>Reference in APA format</th><td colspan="2"></td></tr>
<tr><th>URL of the Reference</th><th>Authors Names and Emails</th><th>Keywords in this Reference</th></tr>
<tr><td>https://doi.org/10.3390/ijerph19127384</td><td>Raj Gururajan, Xujuan Zhou, Yuefeng Li, Chee Keong Wee, Xiaohui Tao, Nathan Wee</td><td>NLP,Triaging,Healthcare AI,Machine Learning</td></tr>
<tr><th>The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)</th><th>The Goal (Objective) of this Solution & What is the problem that need to be solved</th><th>What are the components of it?</th></tr>
<tr><td>Machine Learning Techniques for Medical Referral Triaging</td><td>The goal is to enhance the triaging process of medical referrals by utilizing machine learning techniques that adapt to the Clinical Prioritisation Criteria (CPC) in Queensland, Australia, without relying on historical datasets. The problem addressed is the inefficiency and manual nature of current triaging processes.</td><td>Machine Learning Techniques: Used for classification and triaging.
Natural Language Processing (NLP): Applied to process unstructured referral texts.
Cloud Services: Leveraged for data processing and model deployment.</td></tr>
<tr><th colspan="3">The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process</th></tr>
</table>

The study presents a machine learning-based approach for triaging medical referrals in Queensland, Australia, utilizing Clinical Prioritisation Criteria (CPC). By applying Natural Language Processing (NLP) to convert unstructured referral texts into structured data, the method achieves a high Micro F1 score of 0.98, significantly improving classification accuracy. This system processes around two million referrals annually, enhancing efficiency and ensuring timely patient care without relying on historical datasets. Overall, it addresses the challenges of traditional triaging methods and supports healthcare professionals in making informed decisions.

	Process Steps	**Advantage**	**Disadvantage (Limitation)**
1	Feature extraction using NLP	Converts unstructured referral texts into structured data for analysis.	Requires sophisticated NLP models which can be complex to implement.
2	Machine learning classification	Achieves high accuracy in triaging referrals (Micro F1 score = 0.98).	Dependent on the quality of input data; poor data can lead to inaccurate predictions.
3	Real-time processing of referrals	Enables timely triaging decisions, improving patient care efficiency.	Implementation may require significant computational resources and infrastructure.

Major Impact Factors in this Work

The integration of machine learning with clinical prioritisation criteria enhances decision-making in healthcare, leading to improved patient outcomes and more efficient use of medical resources. Variable Relationships:

Dependent Variable	**Independent Variable**	**Moderating variable**	**Mediating (Intervening) variable**
Accuracy of medical referral triaging.	Features extracted from medical referral texts.	Clinical prioritisation criteria affecting triage decisions.	NLP processing that transforms unstructured text into usable data for classification.

Relationship Among The Above 4 Variables in This article

Input and Output	**Feature of This Solution**	**Contribution & The Value of This Work**
	The study presents a machine learning approach for triaging medical referrals	This research contributes to the automation of the medical referral triaging process by integrating

<table>
<tr>
<td colspan="2"><table><tr><th>Input</th><th>Output</th></tr><tr><td>Unstructured medical referral texts.</td><td>Categorised referrals based on urgency levels as per CPC.</td></tr></table></td>
<td>in Queensland, Australia, utilizing Clinical Prioritisation Criteria (CPC). This system employs Natural Language Processing (NLP) to convert unstructured referral texts into structured data, achieving a high Micro F1 score of 0.98. By processing approximately two million referrals annually, it enhances efficiency and supports timely decision-making in patient care.</td>
<td>machine learning and NLP, thereby improving efficiency and accuracy in healthcare service delivery.</td>
</tr>
<tr>
<th colspan="3">Positive Impact of this Solution in This Project Domain</th>
<th>Negative Impact of this Solution in This Project Domain</th>
</tr>
<tr>
<td colspan="3">Enhances the speed and accuracy of medical referral triaging, leading to better patient management and resource allocation within healthcare systems</td>
<td>Potential challenges include increased complexity in managing data inputs and the need for ongoing updates to machine learning models as clinical criteria evolve.</td>
</tr>
<tr>
<th colspan="2">Analyse This Work By Critical Thinking</th>
<th>The Tools That Assessed this Work</th>
<th>What is the Structure of this Paper</th>
</tr>
<tr>
<td colspan="2">The proposed solution effectively addresses the limitations of traditional triaging methods by leveraging advanced AI techniques, although it requires careful consideration regarding data quality and system integration.</td>
<td>Machine Learning Algorithms (e.g., SVM, Random Forest)

Natural Language Processing Techniques

Evaluation Metrics (e.g., Micro F1 Score)</td>
<td>I. Abstract
II. Introduction
III. Proposed Approach
IV. Related Works
V. Results
VI. Discussion
VII. Conclusion</td>
</tr>
<tr>
<th colspan="4">Diagram/Flowchart</th>
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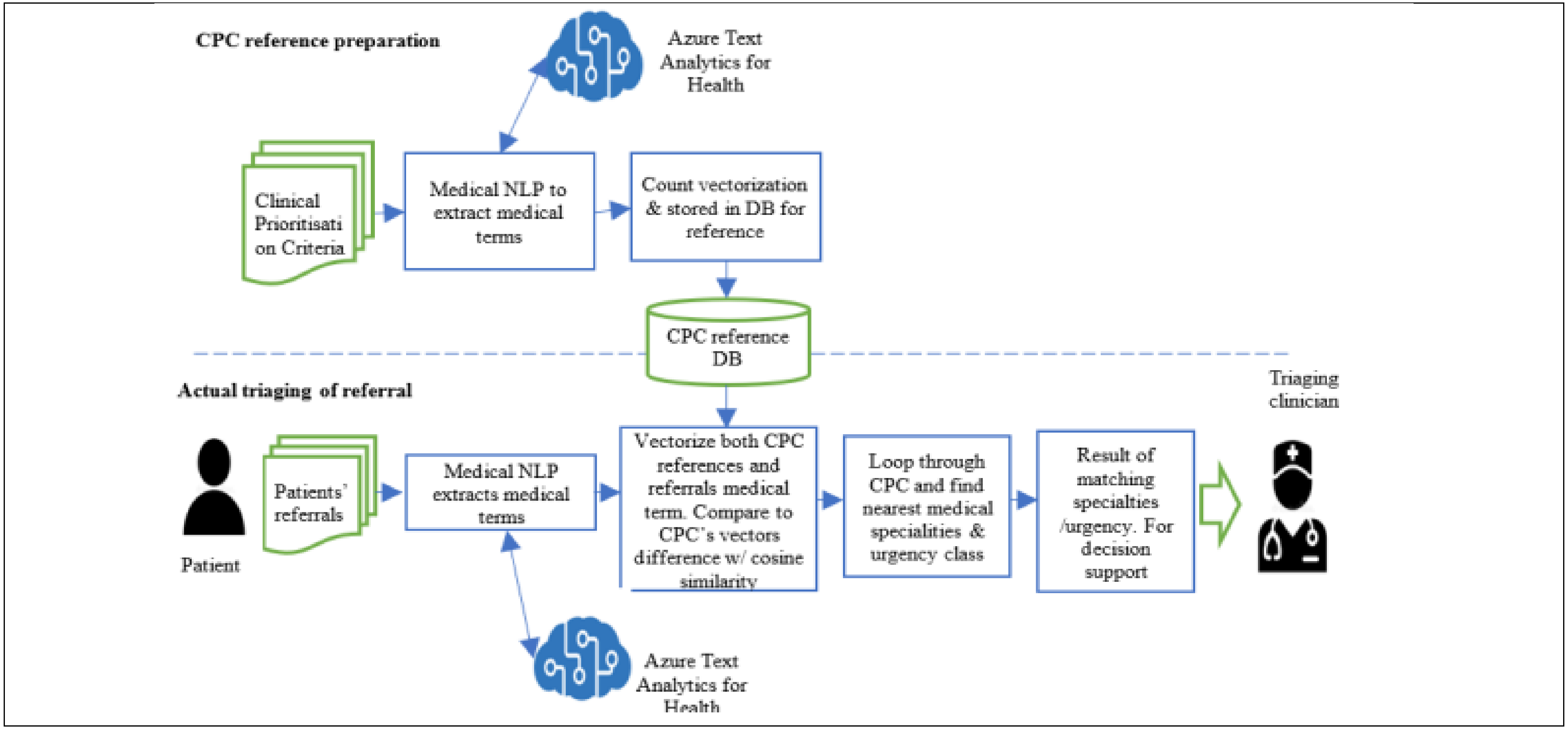

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14		
Reference in APA format		
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
https://doi.org/10.1038/s41591-023-02728-3	Matthew Groh , Omar Badri ,Roxana Daneshjou , Arash Koochek ,Caleb Harris , Luis R. Soenksen , P. Murali Doraiswamy , Rosalind Picard	Deep learning, decision support, skin disease diagnosis, teledermatology, diagnostic accuracy, skin tones.
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)	**The Goal (Objective) of this Solution & What is the problem that need to be solved**	**What are the components of it?**
Deep Learning-Aided Decision Support for Skin Disease Diagnosis	The goal of this solution is to enhance diagnostic accuracy for skin diseases among physicians by utilizing deep learning systems (DLS) as decision support tools. This addresses the problem of systematic errors in diagnoses, particularly for underrepresented populations with darker skin tones.	Deep Learning System (DLS): Utilizes neural network architectures designed to classify various skin diseases. Clinical Decision Support Interface: Provides physicians with options to update their differential diagnoses based on DLS suggestions. Image Dataset: A collection of 364 images representing 46 different skin diseases across diverse skin tones. Evaluation Metrics: Measures diagnostic accuracy through top-1, top-3, and top-4 accuracy assessments.
The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process		
The system employs a digital experiment to evaluate the impact of DLS on diagnostic accuracy among physicians.		

	Process Steps	Advantage	Disadvantage (Limitation)
1	Digital Experiment Setup	Engages a large number of physicians from diverse backgrounds to assess diagnostic accuracy.	May introduce variability in results based on physician experience and biases.

2	Image Presentation	Utilizes a wide range of images to ensure comprehensive evaluation across different skin tones.	Limited clinical context may affect diagnosis accuracy compared to in-person evaluations.
3	DLS Integration	Enhances diagnostic accuracy by providing real-time decision support based on algorithmic predictions.	Potential over-reliance on DLS could lead to misdiagnosis if algorithms are biased or inaccurate.
4	Evaluation Metrics	Provides clear metrics for assessing the effectiveness of physician-DLS partnerships in diagnostics.	The effectiveness may vary significantly depending on physician expertise and familiarity with DLS.

Major Impact Factors in this Work

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
Diagnostic accuracy of skin disease identification.	Use of deep learning decision support systems.	Physician expertise level, experience with diverse skin tones.	Quality of training data and representation of different skin tones in datasets.

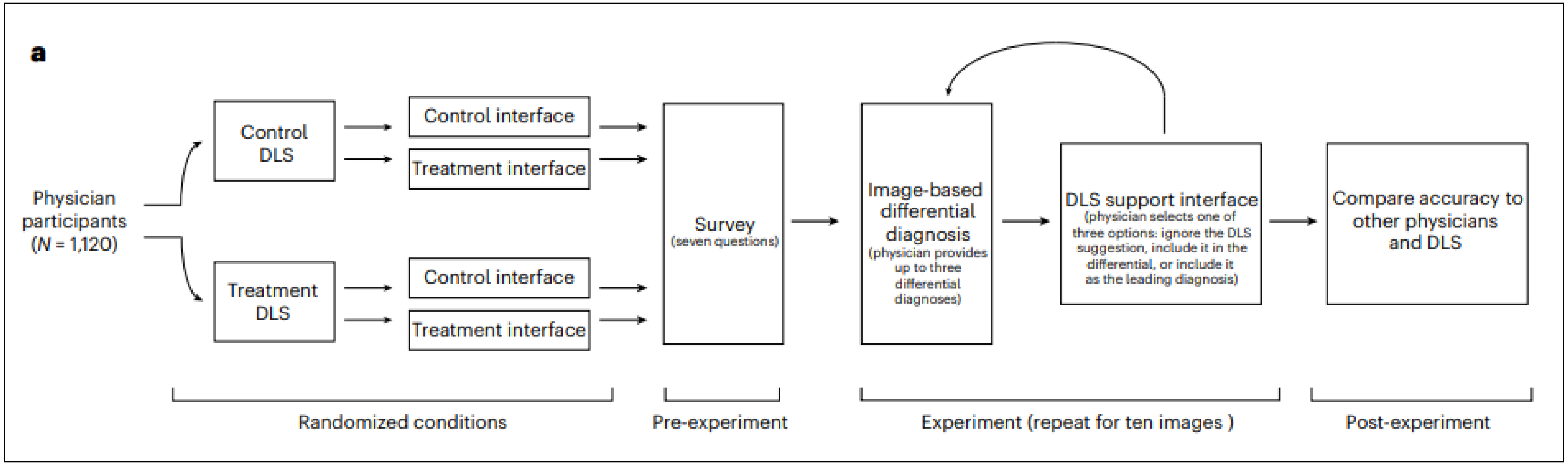
Relationship Among The Above 4 Variables in This article
The study investigates how the integration of DLS influences diagnostic outcomes while considering physician expertise and experience with diverse patient populations as moderating factors.

Input and Output	Feature of This Solution	Contribution in This Work

<table>
<tr><td colspan="2">

Input	Output
Images of inflammatory skin diseases.	Differential diagnoses provided by physicians.

</td><td colspan="2">This solution features a structured approach to integrating deep learning into dermatological diagnostics, aiming to improve accuracy while addressing biases related to skin tone representation.</td><td>The study contributes by demonstrating that DLS can significantly enhance diagnostic performance among physicians but also highlights persistent biases that need addressing within AI systems used in healthcare.</td></tr>
<tr><td colspan="3">Positive Impact of this Solution in This Project Domain</td><td colspan="2">Negative Impact of this Solution in This Project Domain</td></tr>
<tr><td colspan="3">The positive impact includes improved diagnostic accuracy through enhanced physician-machine collaboration, particularly benefiting generalists and specialists alike.</td><td colspan="2">Potential negative impacts include the risk of exacerbating existing biases if DLS are not trained on sufficiently diverse datasets or if physicians become overly reliant on algorithmic suggestions.</td></tr>
<tr><td>Analyse This Work By Critical Thinking</td><td colspan="3">The Tools That Assessed this Work</td><td>What is the Structure of this Paper</td></tr>
<tr><td>The analysis emphasizes the importance of understanding both the capabilities and limitations of AI in clinical settings, particularly regarding bias in medical diagnostics across different populations.</td><td colspan="3">Deep Learning Systems (DLS)
Teledermatology Simulation Techniques
Diagnostic Accuracy Metrics</td><td>1. Abstract
2. Introduction
3. Methods
4. Results
5. Discussion
6. Conclusion</td></tr>
<tr><td colspan="5">Diagram/Flowchart</td></tr>
</table>



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15		
Reference in APA format		
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
https://doi.org/10.3389/fmed.2021.670300	Mara Giavina-Bianchi ,Eduardo Cordioli , André P. dos Santos	Deep neural networks, triage, skin diseases, primary care, teledermatology, artificial intelligence.
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)	**The Goal (Objective) of this Solution & What is the problem that need to be solved**	**What are the components of it?**
Deep Neural Network for Triaging Common Skin Diseases	The goal of this solution is to enhance the accuracy of skin disease diagnosis and referral by utilizing deep neural networks (DNNs) as a triage tool in primary care settings. This addresses the challenge of limited access to dermatological care and the difficulty primary care physicians face in diagnosing various dermatoses accurately.	Deep Neural Networks (DNNs): Various architectures tested for accuracy in diagnosing skin diseases. Image Dataset: Utilizes 140,446 images from a teledermatology project with labeled clinical diagnoses. Referral System: Classifies cases for biopsy, in-person dermatologist visits, or monitoring via teledermatology. Evaluation Metrics: Measures diagnostic accuracy for diagnosis, referral correctness, and priority level.

The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process

The study evaluates different DNN architectures to determine their effectiveness in triaging skin diseases based on image analysis.

	Process Steps	**Advantage**	**Disadvantage (Limitation)**
1	Dataset Acquisition	Large dataset (140,446 images) enhances model training and validation capabilities.	Limited to chronic skin conditions; may not generalize to acute cases.

2	Neural Network Development	Various architectures tested (GoogLeNet, VGG, ResNet) to find the most accurate model.	Complexity in model selection and potential overfitting issues.
3	Training and Validation	High accuracy achieved (89.72% for diagnosis) improves confidence in automated triage systems.	Requires substantial computational resources and time for training.
4	Evaluation of Referrals	Accurate classification aids in appropriate referrals, optimizing patient access to specialists.	Dependence on quality and representativeness of training data for generalization.

Major Impact Factors in this Work

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
Accuracy of skin disease diagnosis and referral.	Utilization of deep neural networks.	Physician experience and familiarity with DNNs.	Quality of images and diversity in skin conditions represented.

Relationship Among The Above 4 Variables in This article
The study examines how DNN performance influences diagnostic outcomes while considering physician expertise and image quality as moderating factors.

Input and Output	Feature of This Solution	Contribution in This Work

<table>
<tr>
<td><table><tr><th>Input</th><th>Output</th></tr><tr><td>Images of skin lesions.</td><td>Diagnosis and referral recommendations based on DNN analysis.</td></tr></table></td>
<td colspan="2">The solution features a comprehensive DNN-based triage system that can assist primary care physicians by providing accurate diagnoses and appropriate referrals for skin diseases.</td>
<td>This research contributes to the field by demonstrating that DNNs can effectively triage common chronic skin diseases, potentially improving patient access to dermatological care through enhanced diagnostic processes.</td>
</tr>
<tr>
<th colspan="2">Positive Impact of this Solution in This Project Domain</th>
<th colspan="2">Negative Impact of this Solution in This Project Domain</th>
</tr>
<tr>
<td colspan="2">The positive impact includes improved efficiency in healthcare delivery by streamlining the referral process from primary care to dermatology.</td>
<td colspan="2">Potential negative impacts include reliance on automated systems that may not account for all clinical nuances or acute conditions.</td>
</tr>
<tr>
<th>Analyse This Work By Critical Thinking</th>
<th colspan="2">The Tools That Assessed this Work</th>
<th>What is the Structure of this Paper</th>
</tr>
<tr>
<td>The analysis emphasizes the importance of integrating AI tools like DNNs into primary care while addressing challenges related to data quality and algorithmic bias.</td>
<td colspan="2">Deep Neural Networks (DNNs)
Teledermatology Techniques
Diagnostic Accuracy Metrics</td>
<td>1. Abstract
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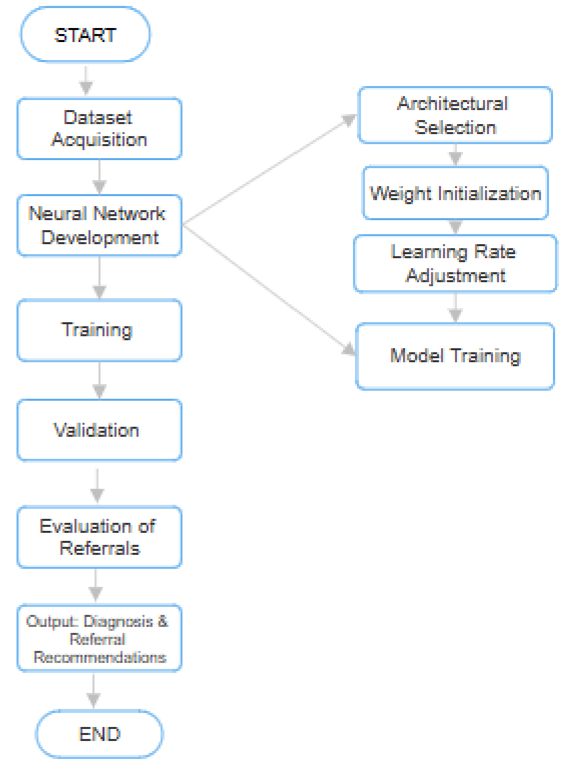

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Work Evaluation Table

<Use the same factors you have used in "Work Evaluation Table" to build your own "Proposed and Previous comparison table ">

Work Goal	System's Components	System's Mechanism	Features /Characteristics	Cost	Speed	Security	Performance	Advantages	Limitations /Disadvantages	Platform	Results
"RapidDiagnosis"	Preprocessing Module, ResNet Feature Extraction and Classification, Output Module	The system preprocesses skin images and uses ResNet to classify conditions, outputting a label with confidence scores to support quick decisions. An optional feedback loop refines the model over time.	The **SkinAI** system provides accurate skin condition classification using ResNet, delivering quick results with clear confidence scores for efficient triage. It ensures data privacy compliance and includes an optional feedback loop for continuous model improvement	**Moderate**	The cost of the **SkinAI** system includes infrastructure, cloud services, data storage, and ongoing maintenance for model updates and privacy compliance. .	The **SkinAI** system ensures security through encrypted data storage, secure communication protocols, and compliance with data privacy regulations to protect patient information. .	The **SkinAI** system delivers high performance with fast image processing and accurate skin condition classification using ResNet, ensuring reliable results with minimal latency for real-time triage.	The **SkinAI** system offers high accuracy, real-time processing, and secure data handling for efficient dermatological triage.	The **SkinAI** system may be limited by the quality of training data, requires significant computational resources, and may struggle with poor-quality input images.	The **SkinAI** system can be deployed on cloud platforms such as AWS, Azure, or Google Cloud for scalable computation and storage, or on local servers for more controlled environments.	The **SkinAI** system provides the disease name (e.g., melanoma, basal cell carcinoma) along with a recommendation indicating whether urgent treatment is needed based on the classification confidence and severity of the condition.