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Skin Disease Classification Using Multi-Model Optimization and Augmentation

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Abstract: Skin diseases affect millions globally, posing screening challenges due to complex lesion characteristics and limited access to medical expertise. Traditional screening methods are time consuming, often requiring extensive laboratory testing. Deep learning and machine learning techniques have gained significant traction in recent years, serving as powerful tools in tackling complex problems, particularly in areas requiring substantial prior knowledge, such as biomedicine. With the challenge of inadequate medical resources, these methods have found impactful applications in disease screening, emerging as a pivotal research focus on dermatology. This project aims to develop an automated skin disease screening system using machine learning and deep learning techniques. The system is designed to accurately identify skin diseases, enhance early detection, address existing challenges in screening and ensure accessibility and affordability for all. This provides a concise review of the classification of skin diseases, leveraging Convolutional Neural Networks (CNN) and K-Nearest Neighbors (KNN) to analyse skin lesion characteristics and evaluate imaging technologies. By exploring the strengths of CNNs due to its high performance in image classification and feature extraction. KNN providing evidence by identifying similar images, making it an explainable AI model. This study presents an Evidence based screening system a virtual dermatology platform leveraging cutting-edge artificial intelligence and deep learning techniques for efficient skin disease classification. Using pre-trained models like GoogleNet, EfficientNet, ResNet, DenseNet, MobileNet and achieving a classification accuracy of 97% through EfficientNet. significantly reducing screening time and cost. The proposed system optimizes preprocessing, transfer learning, model training and cross-validation, significantly improving accuracy. The results highlight AI's potential to revolutionize dermatological screening, reducing costs and improving early detection.

Keywords: Convolutional Neural Network; K-Nearest Neighbors; Evidence based screening; EfficientNet;

I. INTRODUCTION

The skin, the largest and most sensitive part of the human body, is vulnerable to diseases caused by genetics, immune disorders, infections, and environmental factors. Skin anomalies can often signal underlying health issues, making early detection and accurate screening is critical to preventing complications.

Skin diseases are a significant global health concern, with over 3,000 known disorders affecting millions worldwide. Screening and diagnosing these diseases accurately are a challenging task due to the complexity of skin lesion characteristics, low contrast, and visual similarity between different conditions. Traditional screening methods are time-consuming, requiring extensive laboratory testing and high-level medical expertise, making them inaccessible to many. The increasing demand for efficient, automated screening tools has led to the adoption of artificial intelligence (AI) and deep learning techniques in dermatology. Convolutional Neural Networks and machine learning models like K-Nearest Neighbors have emerged as powerful tools for medical image analysis, demonstrating high accuracy in feature extraction and classification tasks.

This project aims to classify skin diseases using advanced models such as Convolutional Neural Networks for image classification and K-Nearest Neighbors to provide supporting evidence for the classifications. The methodology encompasses comprehensive steps, including data exploration, preprocessing, augmentation, feature and label extraction and model training. The process emphasizes selecting the best-performing model based on accuracy through rigorous evaluation and training, including 3-fold, 5-fold, and 10-fold cross-validation. KNN is utilized to enhance the reliability of the classifications by offering evidence-based insights. Finally, an intuitive interface has been developed for an evidence-driven screening system, enabling efficient and accurate skin disease classification.

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The system successfully classifies multiple skin disease categories, including Actinic Keratosis, Atopic Dermatitis, Benign Keratosis, Dermatofibroma, Melanocytic Nevus, Melanoma, Squamous Cell Carcinoma, Tinea Ringworm Candidiasis, and Vascular Lesions. This work underscores the potential of AI-driven dermatological screening systems to bridge the gap in medical resource availability and improve early detection and treatment outcomes.

II. LITERATURE SURVEY

[1], [4], and [8] focus on CNN-based classification using architectures like EfficientNetV2, AlexNet, and ECOC-SVM hybrids to detect a limited set of skin diseases. While these models achieve reasonable accuracy by leveraging deep features, they are confined to narrow disease categories and rely on single or fixed model architectures, which limits adaptability to diverse dermatological conditions. [2] and [6] adopt multi-stage pipelines incorporating segmentation and classification phases using Full-Resolution CNNs, Inception variants, and Decision Trees. These integrated methods improve diagnostic performance by emphasizing lesion localization and data preprocessing. However, their complexity, dependency on large, annotated datasets, and interpretability challenges hinder practical deployment. [3] and [7], along with [17] and [24], propose lightweight or hybrid CNN models such as MobileNetV2 combined with LSTM, DenseNet, or attention mechanisms to achieve efficient classification suitable for mobile deployment. Despite promising performance and reduced computational overhead, these models remain sensitive to lighting conditions and input quality, and their increased architectural complexity may still pose issues for real-time use in resource-constrained environments.

[5] and [12] emphasize broader disease coverage or hybrid human-AI systems. [5] uses MobileNetV2 to classify eight infectious skin diseases, while [12] enhances diagnostic accuracy by integrating EfficientNetB3 with human expert inputs. However, both suffer from lack of clinical feedback integration — [5] misses treatment linkage, and [12] limits scalability due to human dependence. [9], [13], and [15] apply combinations of CNN, LSTM, or transfer learning models like VGG16/19 to psoriasis or cancer datasets, achieving high accuracy. Yet, all rely heavily on public datasets without real clinical validation or expert-reviewed annotations, affecting generalizability to real-world settings. [10] and [18] involve traditional ML or GUI-driven tools using KNN or CNN with regularizes for classification. While user-friendly and interpretable, they are less scalable and sensitive to data noise or size, limiting their robustness for clinical deployment. [11], [14], [22], and [25] introduce more sophisticated architectures including multi-scale attention CNNs, Vision Transformers, deep feature fusion models, and large-scale ResNet fine-tuning for improved accuracy across broader skin disease classes. Despite their high performance (often exceeding 95% accuracy), the need for massive, labelled datasets and intensive computation remains a barrier to deployment in real-time or low-resource environments.

[16], [19], [20], and [21] demonstrate models that approach or surpass dermatologist-level classification by using deep CNNs on extensive clinical or dermoscopic datasets. These studies validate the power of deep learning in dermatology but also highlight the significant reliance on data diversity, labelling quality, and computational infrastructure, which are often unavailable in under-resourced clinical settings. [23] and [24] propose optimization-enhanced deep models such as D2LFS2Net and attention-augmented MobileNet-V2 for skin lesion diagnosis, showing high precision. Nonetheless, their complex model design and reliance on optimization algorithms can hinder real-time responsiveness and ease of deployment in live clinical environments.

To overcome these limitations, this research introduces a multi-model optimization approach with five CNN-based models with K-Nearest Neighbors for evidence-based and explainable AI framework. Unlike previous studies that rely on a single architecture or limited disease categories, our method applies data augmentation, transfer learning, and hyperparameter tuning to improve classification accuracy across multiple skin disease types. By integrating explainable AI with KNN, this approach enhances interpretability and clinical decision-making, bridging the gap between deep learning predictions and dermatologist insights. The proposed method ensures higher classification accuracy, improved generalization, and scalability, addressing the drawbacks observed in prior studies.

III. METHODOLOGY

A. Data understanding and Preprocessing

The process of preparing data for skin disease classification involves two critical steps: data preprocessing and data augmentation, as illustrated in Fig 2. In the data preprocessing stage, a universal dataset sourced from Kaggle, comprising 900 raw images, was utilized. These images were categorized into nine distinct skin disease classes, as shown in Fig 1. Metadata such as image height, width, and mode were extracted to understand the dataset structure. To standardize the dataset, images were resized to uniform dimensions, pixel values were normalized to improve model convergence, and images were converted into tensors to facilitate efficient training.

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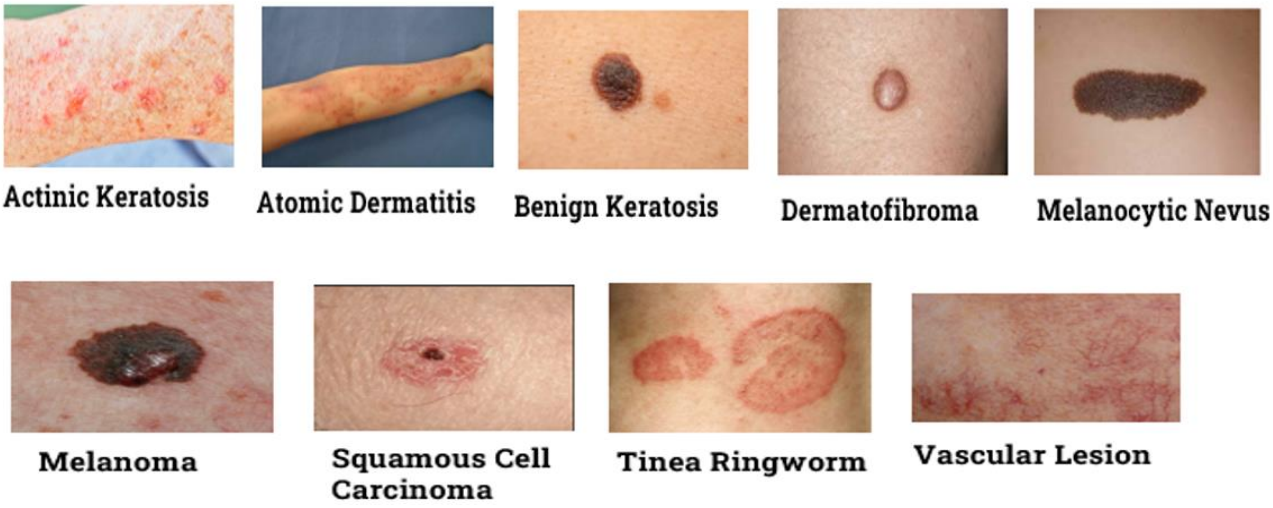

Fig 1. Classification of Skin disease images

Following this, data augmentation techniques were applied to expand the dataset and improve model generalization. Transformations such as rotation, flipping, cropping, inversion, and colour adjustments were employed to introduce variations in the dataset, ensuring the model learns to recognize skin diseases under different lighting conditions and orientations. These preprocessing and augmentation steps significantly enhance the dataset's quality, optimizing it for training a robust and accurate skin disease classification model.

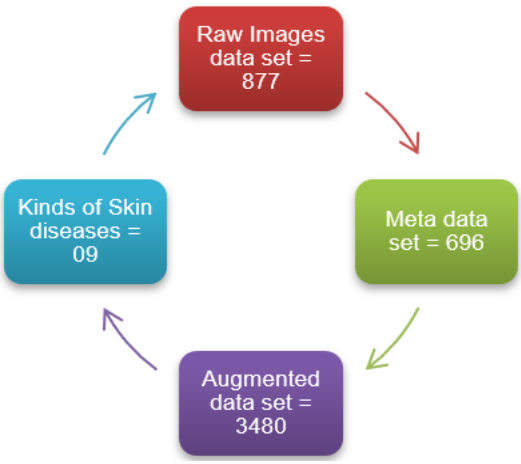

Fig 2. Data preprocessing

B. Model Experiments

After the data preprocessing, then comes the model training, evaluation and deployment as shown in Fig 3. For Model training five deep learning models were considered namely: ResNet, DenseNet, MobileNet, GoogleNet, and EfficientNet. The dataset was split into training and validation sets (80:20). Each model has been evaluated using metrics such as accuracy, precision, recall, f1-score and training accuracy, validation accuracy, training loss and validation loss. Implement early stopping to avoid overfitting of the model. Later, save the best-performing model based on the average accuracy of the model. Then evaluation of the model through Cross-validation (3, 5, and 10 folds) was performed to ensure robustness.

The model experiment began with training and evaluating ResNet, achieving an accuracy of 86.21%. The model showed reliable classification for Benign Keratosis (0.95), Tinea Ringworm Candidiasis (0.96), and Atopic Dermatitis (0.94). However, Melanoma (0.69) and Squamous Cell Carcinoma (0.74) had lower recall, indicating room for improvement. The macro and weighted averages of 0.86 and 0.87, respectively, confirm a balanced performance.

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Enhancing melanoma and carcinoma detection through data augmentation or class balancing could improve accuracy. Next, MobileNet achieved an improved accuracy of 93.68%, with high F1-scores for Benign Keratosis (0.97), Tinea Ringworm Candidiasis (0.98), and Atopic Dermatitis (0.99), demonstrating strong classification reliability. Melanoma (0.87) and Squamous Cell Carcinoma (0.88) showed notable improvements. The macro and weighted averages of 0.94 indicate a well-balanced model with strong generalization, suggesting that optimization techniques and augmentation strategies effectively enhance performance. DenseNet achieved an accuracy of 86.35%, showing reliable performance across multiple classes. High F1-scores for Benign Keratosis (0.96), Atopic Dermatitis (0.93), and Tinea Ringworm Candidiasis (0.94) confirm their classification strength. However, Actinic Keratosis (0.76) and Squamous Cell Carcinoma (0.69) had lower F1-scores due to low recall, indicating challenges in detecting these conditions. The macro and weighted averages of 0.88 and 0.89 reflect a balanced model, though recall improvements could further enhance accuracy. For GoogleNet, an accurate score of 96.26% was achieved, marking significant improvement. Vascular Lesion (1.00), Actinic Keratosis (0.97), and Atopic Dermatitis (0.98) demonstrated excellent F1-scores, while Melanoma (0.92) and Dermatofibroma (0.94) also showed strong classification performance. The macro and weighted averages of 0.96 indicate a well-balanced model, making it highly effective for skin disease diagnosis.

RESNET18

Accuracy	0.8621			
Classes	Precision	Recall	F1-score	Support
Actinic keratosis	0.85	0.94	0.9	86
Atopic Dermatitis	0.96	0.93	0.94	83
Benign keratosis	0.97	0.94	0.95	79
Dermatofibroma	0.97	0.75	0.85	93
Melanocytic nevus	0.84	0.79	0.81	84
Melanoma	0.76	0.63	0.69	71
Squamous cell carcinoma	0.67	0.83	0.74	60
Tinea Ringworm Candidiasis	0.95	0.97	0.96	65
Vascular lesion	0.79	0.99	0.88	75

MOBILENET

Accuracy	0.9368			
Classes	Precision	Recall	F1-score	Support
Actinic keratosis	0.91	0.97	0.94	86
Atopic Dermatitis	0.98	1	0.99	83
Benign keratosis	0.99	0.96	0.97	79
Dermatofibroma	0.98	0.86	0.91	93
Melanocytic nevus	0.85	0.96	0.91	84
Melanoma	0.95	0.8	0.87	71
Squamous cell carcinoma	0.82	0.93	0.88	60
Tinea Ringworm Candidiasis	0.98	0.98	0.98	65
Vascular lesion	0.99	0.96	0.97	75

DENSENET

Accuracy	0.8635			
Classes	Precision	Recall	F1-score	Support
Actinic keratosis	0.98	0.62	0.76	86
Atopic Dermatitis	0.92	0.94	0.93	83
Benign keratosis	0.95	0.96	0.96	79
Dermatofibroma	0.99	0.74	0.85	93
Melanocytic nevus	0.93	0.93	0.93	84
Melanoma	0.87	0.77	0.82	71
Squamous cell carcinoma	0.54	0.95	0.69	60
Tinea Ringworm Candidiasis	0.93	0.95	0.94	65
Vascular lesion	0.84	0.97	0.9	75

GOOGLENET

Accuracy	0.9626			
Classes	Precision	Recall	F1-score	Support
Actinic keratosis	0.95	1	0.97	86
Atopic Dermatitis	0.97	1	0.98	83
Benign keratosis	0.97	0.96	0.97	79
Dermatofibroma	0.98	0.91	0.94	93
Melanocytic nevus	0.94	0.98	0.96	84
Melanoma	0.92	0.93	0.92	71
Squamous cell carcinoma	0.98	0.92	0.95	60
Tinea Ringworm Candidiasis	0.97	0.95	0.96	65
Vascular lesion	1	1	1	75

EFFICIENTNET

Accuracy	0.9799			
Classes	Precision	Recall	F1-score	Support
Actinic keratosis	1	0.97	0.98	86
Atopic Dermatitis	0.99	1	0.99	83
Benign keratosis	0.99	0.96	0.97	79
Dermatofibroma	1	0.99	0.99	93
Melanocytic nevus	0.99	0.98	0.98	84
Melanoma	0.96	0.97	0.97	71
Squamous cell carcinoma	0.92	0.98	0.95	60
Tinea Ringworm Candidiasis	0.97	0.98	0.98	65
Vascular lesion	0.99	0.99	0.99	75

Fig 4. Screenshot displaying the model training output, highlighting deep-dive analysis results for each individual model

Classification Metrics of EfficientNet:

EfficientNet uses a compound scaling method to achieve higher accuracy with fewer parameters, making it more computationally efficient compared to traditional CNN architectures like Res Net and Mobile Net etc. The Efficient Net Model Evaluation Metrics:

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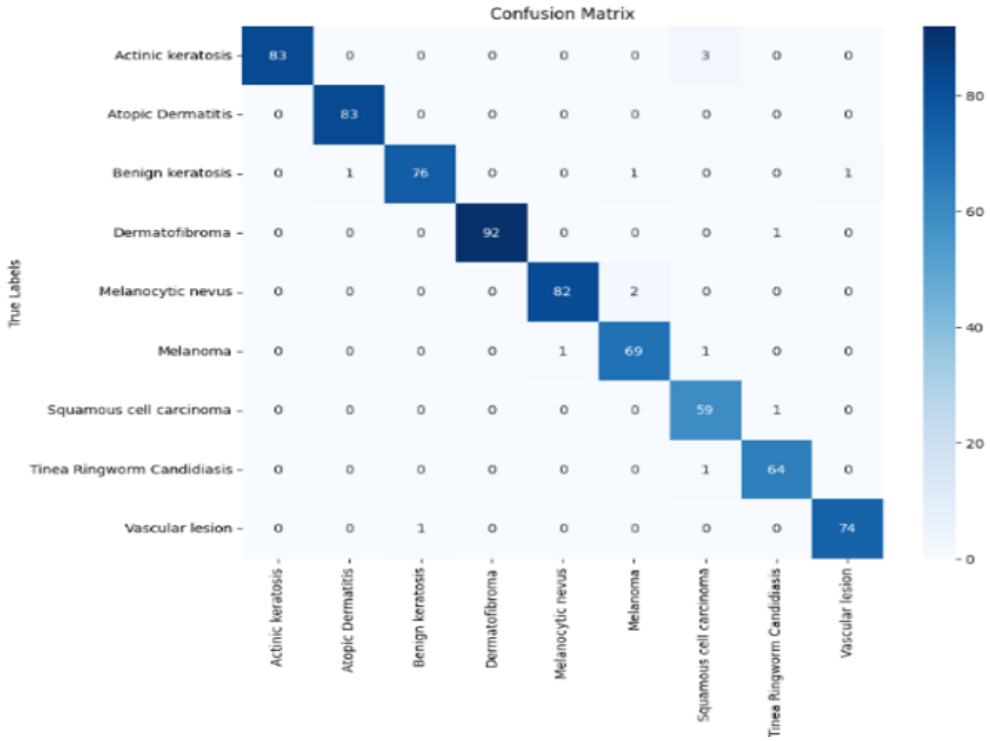
Accuracy: 0.9799

Classification Report:

	precision	recall	f1-score	support
Actinic keratosis	1.00	0.97	0.98	86
Atopic Dermatitis	0.99	1.00	0.99	83
Benign keratosis	0.99	0.96	0.97	79
Dermatofibroma	1.00	0.99	0.99	93
Melanocytic nevus	0.99	0.98	0.98	84
Melanoma	0.96	0.97	0.97	71
Squamous cell carcinoma	0.92	0.98	0.95	60
Tinea Ringworm Candidiasis	0.97	0.98	0.98	65
Vascular lesion	0.99	0.99	0.99	75
accuracy			0.98	696
macro avg	0.98	0.98	0.98	696
weighted avg	0.98	0.98	0.98	696

(a)



(b)

Fig 5. (a) EfficientNet model metrics and (b) Confusion matrix for Efficient model training

This defines key evaluation metrics, including Accuracy, which measures the proportion of correct predictions, and Precision, Recall, and F1-score, which assess different aspects of model performance. Precision measures how many of the predicted positives are actual positives, recall indicates how many actual positives were correctly identified, and the F1-score balances both metrics. Additionally, Macro and Weighted Averages provide a way to summarize performance across multiple classes, with the macro average treating all classes equally and the weighted average considering class imbalance. Fig 5(b) is a confusion matrix, visually representing classification performance by showing the number of correct and incorrect predictions for each class. Beside it, Fig 5(a) is a classification report that provides detailed precision, recall, and F1-scores for individual classes, with an overall accuracy of 97.99%, suggesting strong model performance. High F1-scores across most classes indicate reliable classification. To conclude with, EfficientNet achieved an accuracy of 97.99%, with excellent classification for Vascular Lesion (1.00), Actinic Keratosis (0.97), and Atopic Dermatitis (0.98). Other conditions, including Melanoma (0.92) and Dermatofibroma (0.94), also performed well. The macro and weighted averages of 0.96 indicate strong overall performance, making EfficientNet highly effective for skin disease screening. After multiple training iterations, EfficientNet emerged as the best-performing model, achieving an average accuracy of 97%, demonstrating high performance across various aspects.

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The performance of deep learning models like EfficientNet, GoogleNet, MobileNet, ResNet, and DenseNet using 3-fold, 5-fold, and 10-fold cross validation. The model's accuracy across the three cross-validation schemes and the Table 1 highlights that EfficientNet consistently achieves the highest accuracy, reaching 99% under 10-fold cross validation. Moreover, all models surpass 85% accuracy when evaluated with 10-fold validation, indicating robust and reliable performance. This approach helps mitigate overfitting and provides a more comprehensive assessment of each model's generalization capabilities.

TABLE I CROSS VALIDATION METRICS OF ALL THE MODELS

Model Name	Cross validation		
	3-Fold	5-Fold	10-Fold
EfficientNet	0.97	0.98	0.99
GoogleNet	0.96	0.97	0.98
MobileNet	0.93	0.94	0.95
ResNet	0.86	0.87	0.88
DenseNet	0.86	0.87	0.88

K-Nearest Neighbors (KNN) is a supervised machine learning algorithm that classifies data points based on their similarity to other points in a dataset. In the context of the work conducted, KNN serves as an evidence-based explanation by retrieving visually similar skin lesion images and displaying their respective distance measures. Fig 6 shows a primary skin lesion on the arm, followed by a set of similar images arranged according to how closely they match the query lesion, with lower distance values indicating higher similarity. This process provides transparency in the classification outcome.

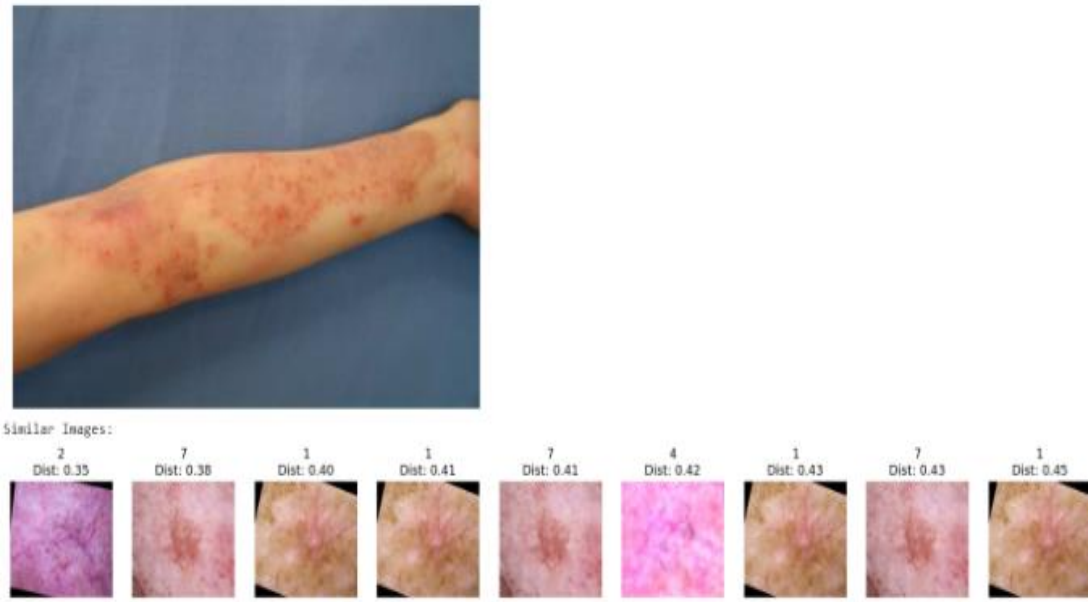

Fig 6. K-Nearest Neighbors for evidence-based explanation

DEPLOYMENT

The workflow depicted in Fig 7 outlines a comprehensive pipeline for skin disease classification using CNN models. The process begins in the Build Phase, where training images undergo Data Preprocessing to standardize dimensions and quality, followed by Image Augmentation to enhance dataset variability with techniques like rotation and flipping etc. The augmented images are passed to a Feature Extractor, generating labels that are fed into Pre-trained Models such as ResNet, DenseNet, MobileNet, GoogleNet, and EfficientNet. Among these, EfficientNet is Fine-Tuned for optimal performance. The refined model undergoes Cross-Validation to ensure robust evaluation and categorization into predefined categories.

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In the Deployment Phase, images are processed through a Data Extractor and passed to the fine-tuned EfficientNet model for classification. The results are integrated into an Interface for Evidence-Based Screening, facilitating an intuitive and accurate screening system. This end-to-end pipeline ensures an efficient and scalable solution for skin disease classification and screening.

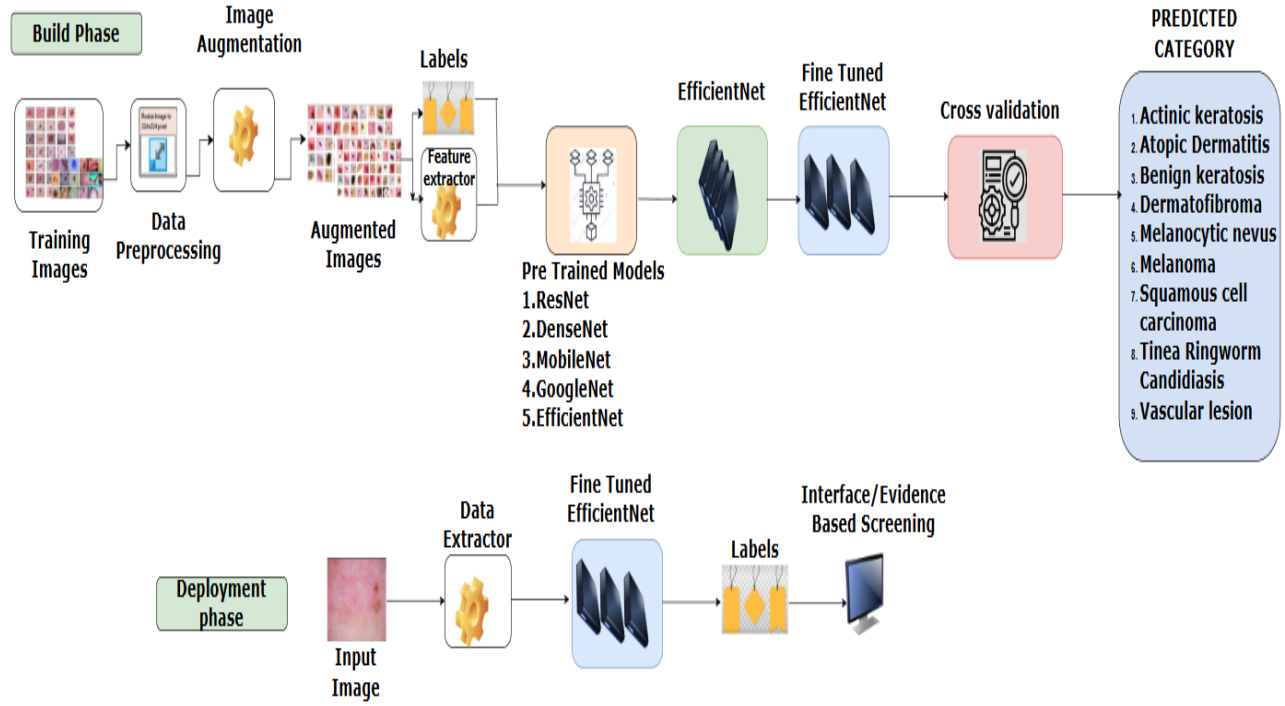

Fig 7. Design and Implementation of Skin disease classification project

IV. RESULTS AND DISCUSSION

The interface showcased in Fig 8 represents an Evidence-Based Screening System for Skin Disease Classification. It is a user-friendly platform designed to classify skin diseases efficiently. Upon uploading an image, the system analyses it and provides a Class Prediction along with a Confidence Score. The interface includes an Evidence-Based Explanation, providing insights into the system's decision-making process, supported by clinical reasoning.

Additionally, it offers a Predicted Class Explanation, describing skin disease characteristics, such as its asymmetry, irregular borders, and colour variations, while emphasizing the urgency of medical intervention. This system is a valuable tool for dermatologists, enabling informed decision-making and improving early detection of critical skin conditions. By this the conclusion is with the combination of CNNs for classification and K-Nearest Neighbors for explainability enhances the system's utility. CNN provides high classification accuracy, while KNN supports evidence-based decision-making by identifying similar images. This hybrid approach ensures both performance and transparency. And EfficientNet demonstrated superior performance with an accuracy of 97%. Cross-validation results confirmed EfficientNet's robustness, particularly with 10-fold validation. And which is used for the skin disease classification project and to build an intuitive interface for evidence-based screening system. This is a significant advancement in dermatological screening, offering an accurate, cost-effective, and efficient solution. By leveraging EfficientNet's high accuracy and integrating explainability features, this system has the potential to transform skin disease classification and screening.

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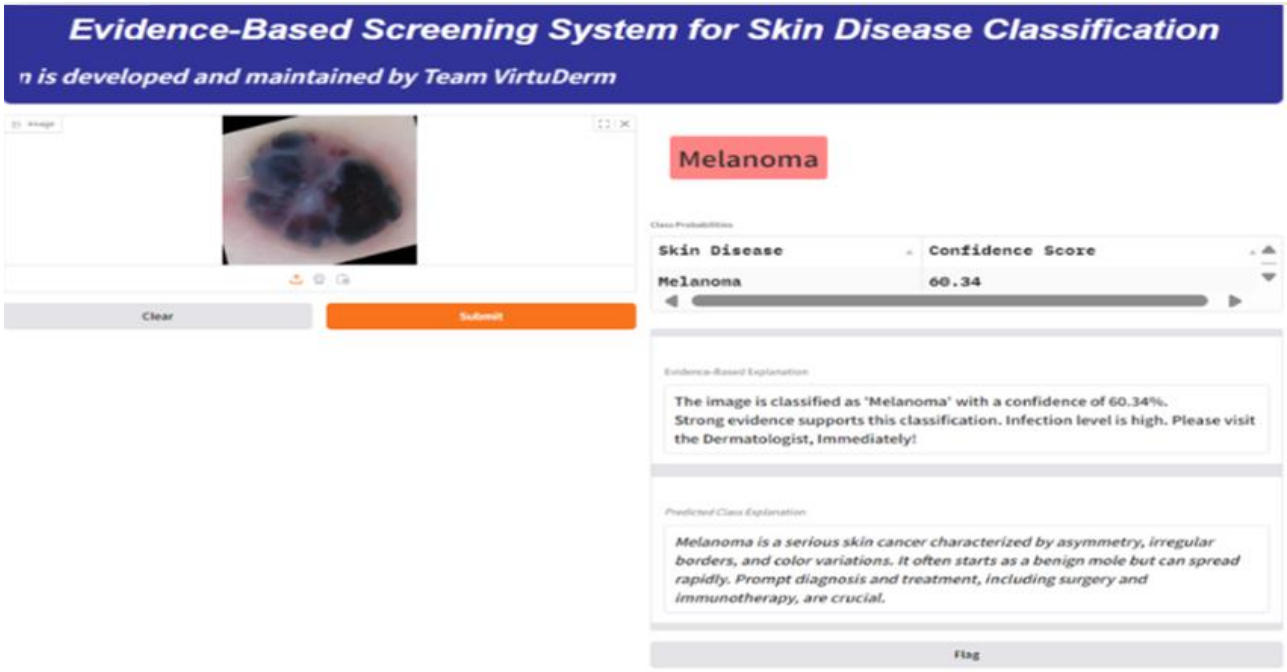

Fig 8. Interface for Evidence based screening system for Skin disease classification

V. CONCLUSION

In conclusion to this study future advancements in the skin disease classification system aim to broaden its capabilities and accessibility through several key enhancements. Federated Learning will enable the model to scale by incorporating distributed learning across diverse datasets while ensuring data privacy and security, thus improving its generalizability across varied demographics. The system's Expanded Scope will include not only additional human skin conditions but also animal skin diseases, making it a versatile tool for both human and veterinary dermatology. Furthermore, introducing Multi-Language Support will facilitate seamless communication between patients and dermatologists in various languages, ensuring inclusivity and accessibility for users worldwide, irrespective of their linguistic background.

In addition, Large Language Models (LLMs) can be integrated to enhance interpretability and patient engagement by providing context-based explanations and personalized insights. LLM-driven chat interfaces can offer real-time guidance on the image capture process, triage user queries, and deliver evidence-based recommendations, further elevating the overall user experience and clinical decision support.

REFERENCES

[1] R. Karthik, T. S. Vaichole, S. K. Kulkarni, O. Yadav, and F. Khan, "Eff2Net: An efficient channel attention-based convolutional neural network for skin disease classification," *Biomedical Signal Processing and Control*, vol. 73, pp. 103406, 2022. doi: 10.1016/j.bspc.2021.103406

[2] M. A. Al-masni, D. H. Kim, and T. S. Kim, "Multiple skin lesions diagnostics via integrated deep convolutional networks for segmentation and classification," *Computer Methods and Programs in Biomedicine*, vol. 190, pp. 105351, 2020. doi: 10.1016/j.cmpb.2020.105351

[3] P. N. Srinivasu, J. G. Sivasai, M. F. Ijaz, A. K. Bhoi, W. Kim, and J. J. Kang, "Classification of skin disease using deep learning neural networks with mobilenet v2 and lstm," *Sensors*, vol. 21, no. 8, pp. 2852, 2021. doi: 10.3390/s21082852

[4] N. Hameed, A. M. Shabut, and M. A. Hossain, "Multi-Class Skin Diseases Classification Using Deep Convolutional Neural Network and Support Vector Machine," *Proc. Int. Conf. Software, Knowledge, Information Management & Applications (SKIMA)*, pp. 1–7, 2018. doi: 10.1109/SKIMA.2018.8631525

[5] A. Furqon, K. Malik, and F. N. Fajri, "Detection of Eight Skin Diseases Using Convolutional Neural Network with MobileNetV2 Architecture for Identification and Treatment Recommendation on Android Application," *Jurnal*

DOI: 10.17148/IJIREEICE.2025.13659

Ilmiah Teknik Elektro Komputer Dan Informatika, vol. 10, no. 2, pp. 373–384, 2024. doi: 10.26555/jiteki.v10i2.28817

[6] A. O. Mulani, G. Birajadar, N. Ivković, B. Salah, and A. R. Darlis, "Deep Learning Based Detection of Dermatological Diseases Using Convolutional Neural Networks and Decision Trees," *Traitement Du Signal*, vol. 40, no. 6, pp. 2819–2825, 2023. doi: 10.18280/ts.400642

[7] W. Wang, Y. Li, T. Zou, X. Wang, J. You, and Y. Luo, "A Novel Image Classification Approach via Dense-MobileNet Models," *Mobile Information Systems*, vol. 2020, pp. 1–8, 2020. doi: 10.1155/2020/7602384

[8] T. Shanthi, R. S. Sabeenian, and R. Anand, "Automatic diagnosis of skin diseases using convolution neural network," *Microprocessors and Microsystems*, vol. 76, pp. 103074, 2020. doi: 10.1016/j.micpro.2020.103074

[9] S. F. Aijaz, S. J. Khan, F. Azim, C. S. Shakeel, and U. Hassan, "Deep Learning Application for Effective Classification of Different Types of Psoriasis," *Journal of Healthcare Engineering*, vol. 2022, pp. 1–12, 2022. doi: 10.1155/2022/7541583

[10] M. Q. Hatem, "Skin lesion classification system using a K-nearest neighbor algorithm," *Visual Computing for Industry, Biomedicine, and Art*, vol. 5, no. 1, 2022. doi: 10.1186/s42492-022-00103-6

[11] H. Liu, Y. Dou, K. Wang, Y. Zou, G. Sen, and H. Li, "A skin disease classification model based on multi-scale combined efficient channel attention module," *Scientific Reports*, vol. 15, p. 6116, 2025. doi: 10.1038/s41598-025-90418-0

[12] D. Ajabani, Z. A. Shaikh, A. Yousef, K. Ali, and M. A. Albahar, "Enhancing skin lesion classification: a CNN approach with human baseline comparison," *PeerJ Computer Science*, vol. 2025, no. 2795, 2025. doi: 10.7717/peerj-cs.2795

[13] A. Faghihi, M. Fathollahi, and R. Rajabi, "Diagnosis of Skin Cancer Using VGG16 and VGG19 Based Transfer Learning Models," *arXiv preprint*, arXiv:2404.01160, 2024. [Online]. Available: https://arxiv.org/abs/2404.01160

[14] G. M. S. Himel, M. M. Islam, K. A. Al-Aff, S. I. Karim, and M. K. U. Sikder, "Skin Cancer Segmentation and Classification Using Vision Transformer for Automatic Analysis in Dermatoscopy-based Non-invasive Digital System," *arXiv preprint*, arXiv:2401.04746, 2024. [Online]. Available: https://arxiv.org/abs/2401.04746

[15] Z. A. Shaikh, D. Ajabani, A. Yousef, K. Ali, and M. A. Albahar, "Enhancing skin lesion classification: a CNN approach with human baseline comparison," *PeerJ Computer Science*, vol. 2025, no. 2795, 2025. doi: 10.7717/peerj-cs.2795

[16] M. K. Hasan et al., "Dermo-DOCTOR: A framework for concurrent skin lesion detection and recognition using a deep convolutional neural network with end-to-end dual encoders," *arXiv preprint*, arXiv:2102.01824, 2021. [Online]. Available: https://arxiv.org/abs/2102.01824

[17] P. N. Srinivasu, J. G. Sivasai, M. F. Ijaz, A. K. Bhoi, W. Kim, and J. J. Kang, "Classification of skin disease using deep learning neural networks with mobilenet v2 and lstm," *Sensors*, vol. 21, no. 8, pp. 2852, 2021. doi: 10.3390/s21082852

[18] M. A. Albahar, "Skin lesion classification using convolutional neural network with novel Regularizer," *IEEE Access*, vol. 7, pp. 38306–38313, 2019. doi: 10.1109/ACCESS.2019.2907011

[19] A. Esteva et al., "Dermatologist-level classification of skin cancer with deep neural networks," *Nature*, vol. 542, no. 7639, pp. 115–118, 2017. doi: 10.1038/nature21056

[20] T. J. Brinker et al., "A convolutional neural network trained with dermoscopic images performed on par with 145 dermatologists in a clinical melanoma image classification task," *European Journal of Cancer*, vol. 111, pp. 148–154, 2019. doi: 10.1016/j.ejca.2019.02.005

[21] E. Nasr-Esfahani et al., "Melanoma detection by analysis of clinical images using convolutional neural network," in *Proc. IEEE EMBC*, pp. 1373–1376, 2016. doi: 10.1109/EMBC.2016.7591003

[22] T. Akram, S. A. Khan, U. Tariq, and M. Y. Javed, "Dermo-Optimizer: Skin lesion classification using information-theoretic deep feature fusion and entropy-controlled binary bat optimization," *International Journal of Imaging Systems and Technology*, vol. 34, no. 1, p. e23172, 2024. doi: 10.1002/ima.23172

[23] V. Dillshad, M. A. Khan, M. Sharif, and A. R. Javed, "D2LFS2Net: Multi-class skin lesion diagnosis using deep learning and variance-controlled marine predator optimisation: An application for precision medicine," *CAAI Transactions on Intelligence Technology*, 2023. doi: 10.1049/cit2.12267

[24] M. N. Nirupama and B. Virupakshappa, "Attention-augmented MobileNet-V2 with multi-scale feature integration for accurate skin disease classification," *Biomedical Signal Processing and Control*, vol. 87, p. 105340, 2024. doi: 10.1016/j.bspc.2023.105340

[25] S. S. Han, M. S. Kim, W. Lim, G. H. Park, I. Park, and S. E. Chang, "Classification of the Clinical Images for Benign and Malignant Cutaneous Tumors Using a Deep Learning Algorithm," *Journal of Investigative Dermatology*, vol. 138, no. 7, pp. 1529–1538, Jul. 2018. doi: 10.1016/j.jid.2018.01.028.