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DEEP LEARNING-BASED AUTOMATED SKIN DISEASE CLASSIFICATION WITH AN INTEGRATED WEB-BASED CLINICAL DECISION SUPPORT SYSTEM

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Abstract
Skin diseases are among the most prevalent health issues worldwide, ranging from benign conditions to life-threatening cancers. Early and accurate diagnosis is essential for effective treatment; however, the shortage of dermatology specialists, particularly in low-resource regions, makes timely diagnosis challenging. To address this issue, this study proposes an automatic skin disease classification system using deep learning integrated with a web-based clinical decision support system (CDSS). The proposed system classifies ten skin disease categories, including Eczema, Melanoma, Atopic Dermatitis, Basal Cell Carcinoma, Melanocytic Nevi, Benign Keratosis, Psoriasis, Seborrheic Keratosis, Tinea Ringworm, and Warts Molluscum. The dataset is enhanced through extensive image preprocessing, including resizing, normalization, contrast enhancement, and data augmentation, which improves feature representation and reduces overfitting. A comparative evaluation is conducted using CNN, VGG16, ResNet50, InceptionV3, and MobileNetV2 models on dermoscopic images. Experimental results show that all models achieve competitive performance; however, MobileNetV2 outperforms others with an accuracy of 92.8%, precision of 92.4%, recall of 92.0%, and F1-score of 92.2%. In comparison, InceptionV3, ResNet50, VGG16, and CNN achieve accuracies of

88.4%, 87.9%, 86.3%, and 79.1%, respectively. The superior performance of MobileNetV2 is due to its efficient lightweight architecture and strong generalization capability. The system is deployed as a web-based clinical decision support tool for real-time and accessible skin disease prediction, assisting dermatologists in improving diagnostic accuracy and supporting early detection in clinical environments.

INTRODUCTION

Skin diseases are one of the most common medical issues that people of all ages suffer from all over the world. These can include minor infections, inflammation and serious and even life-threatening diseases like melanoma and other forms of skin cancer. The chances of effective treatment and patient survival rely on early and accurate diagnosis. In many developing countries, however, even in rural areas of Pakistan [1] the number of experienced dermatologists is low and this causes late diagnosis and therapy. In recent years, there has been significant success in the field of medical image analysis using artificial intelligence (AI), specifically deep learning. CNNs have proven to be very effective at automatically learning discriminative features from dermoscopic images for the purpose of skin disease classification. Deep networks with robust feature learning capacities like VGG16, ResNet50, InceptionV3 and MobileNetV2 have been studied extensively for medical imaging applications [2].

Despite significant progress, challenges still exist, including class imbalance, image variability, and computational complexity of deep models [3]. Furthermore, most of the current systems are not usable in practice and not clinically integrated, thus preventing their application. To overcome these drawbacks, this study suggests an automatic skin disease classification system of deep learning combined with a web-based CDSS system is proposed. The system classifies ten skin disease categories, including Eczema, Melanoma, Atopic Dermatitis, Basal Cell Carcinoma, Melanocytic Nevi, Benign Keratosis, Psoriasis, Seborrheic Keratosis, Tinea Ringworm, and Warts Molluscum. Multiple deep learning models are analysed and tested on a web-based environment for real time prediction of the best model. This study aims at enhancing the diagnostic performance, minimizing manual diagnosis and creating a user-friendly AI tool to assist dermatologists in clinical decision making.

- **Literature Review**

There have been notable advancements in skin cancer classification using Deep Learning in recent years, with researchers investigating new neural network architectures and transfer learning techniques to enhance diagnostic performance. In recent years, there has been a significant amount of research on the classification of skin cancer using Deep Learning, with researchers exploring new neural network architectures and transfer learning techniques to improve the accuracy of skin cancer classification. Previous works like [4] have shown that the use of some transfer learning models including EfficientNet, DenseNet, and InceptionV3, combined with the preprocessing of the images such as augmentation, normalization, and removing duplicate images provides AUC of up to 80% in ISIC datasets. However, problems with imbalanced, biased and under-robust datasets were reported. Following this, proposed a framework for classification of melanoma based on the risk level with high validation accuracy of AUC > 94%, and EfficientNet-B6 model had high training accuracy. Likewise, [5] proposed a multi-class classification system using EfficientNet, ResNet50, and DenseNet with EAI in order to

enhance the interpretability of the model with an accuracy of more than 90%. As can be seen in the above-mentioned studies, transfer learning is consistently effective, but also some problems with dataset imbalance and low generalization. Ensemble and hybrid learning methods are other advances. [6] gained a better accuracy of more than 94% with an ensemble of CNN, ResNet, and DenseNet models, and [7] combined deep learning with traditional machine learning models with an accuracy of more than 93%. The performance was greatly enhanced but increased computational complexity and restricted real-time applicability were reported for both studies. These results are corroborated by several comparative and review studies. According to [8] the accuracy of deep learning models is typically 85%–95% based on dataset quality and [9] emphasized that deep learning models are superior to traditional machine learning models, with a 95% accuracy if the data set is good. Some problems, however, have persisted, including the lack of standard evaluation protocols and bias in datasets. Recent advancements have been towards real world applicability and advanced architectures. In addition to CNN-LSTM models, some researchers obtained high accuracy for skin disease diagnostic system with using the artificial intelligence by developing a mobile [10] or a multiclass deep learning [2] model with an accuracy of 90% and 93% respectively. In the same way, [12] showed that [More advanced models] outperform CNNs by having an accuracy above 94%. Other studies build upon specific methods. With the dermoscopic structure-based analysis, [5] achieved 91% accuracy, and [13] proposed a fused deep learning architecture that achieved an accuracy of more than 93% with better localization. Even with newer methods, CNN-based models were reported to be equally effective in the binary classification with 85%–90% accuracy as reported in [14]. Last, some systematic studies, like [5] and [15] highlighted the high performance of deep learning (sensitivity of 80% – 96% depending on the application), however the existing challenges (heterogenicity of the used datasets, high computational cost, and limited external validation) still limit its clinical deployment [16]. Based on the literature, it is evident that, overall, transfer learning, ensemble methods, and transformer-based architectures consistently outperform traditional CNN methods with an accuracy between 85% and 95%. Some datasets are highly imbalanced, others overfit, others are too difficult to compute, and none are validated in real-world settings, however, to make the best systems more robust and clinically deployable.

. Material and Methods

.1 Proposed Methodology

The suggested approach is a step-by-step classification of skin diseases from dermoscopic images. First, the data is gathered as images of skin lesions. The images undergo a preprocessing phase, where techniques like resizing, normalization, contrast enhancement, and noise reduction are applied to enhance the quality of the images and bring out the significant visual characteristics [17]. After preprocessing, the enhanced images are fed into deep learning models for feature extraction and classification. Several CNN architectures are used to extract discriminative patterns from the images. Finally, the trained models are tested, and the best of these models is incorporated into a CWSS for the prediction of skin disease in real time in a web-based system. Finally, the trained models are evaluated, and the best of these models is incorporated in a web-based CWSS to predict the skin disease in real-time.

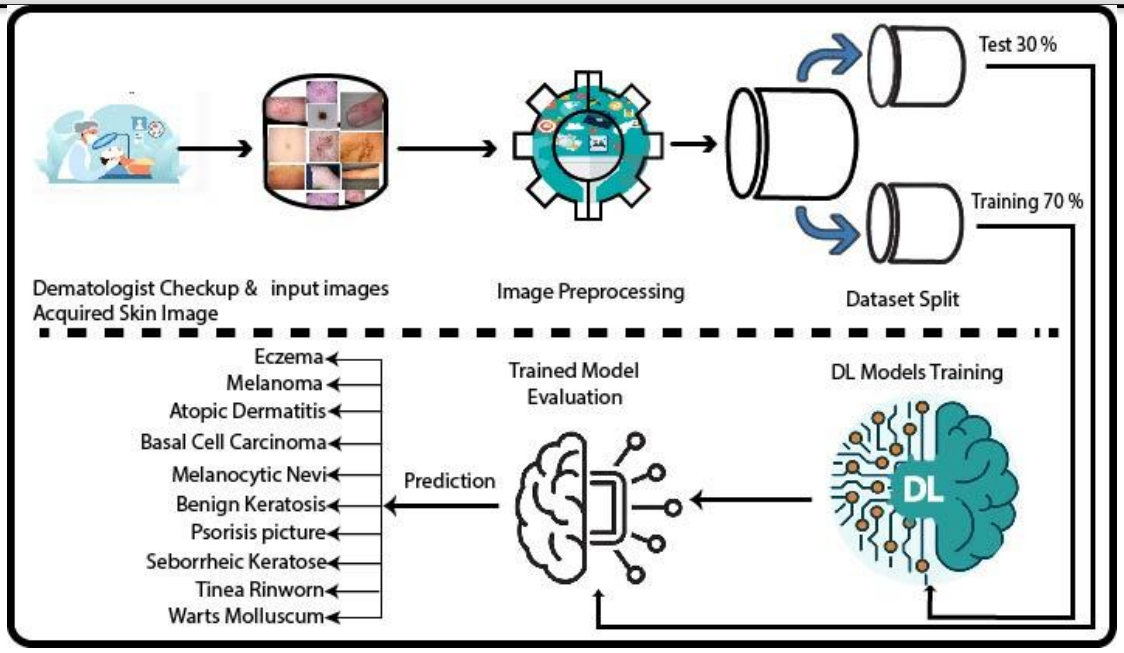

Figure 1: The proposed enhanced research methodology using dermoscopic images through an intelligent deep learning framework.

The dataset is then split into sets of training data and testing data: about 70% of the data is used for training and the remaining 30% is used for testing. This split will allow the effective learning of the models and at the same time provide an independent dataset to fairly test the models' performance [18]. Then, multiple deep learning models are trained in the pre-processed training data. The models learn to identify discriminative features from dermoscopic images to categorize them into several skin disease categories. Once models are trained and tested on the test set to measure the model's accuracy and generalization. Finally, the system generates the classification output based on various skin diseases, which can help in clinical decision-making [19]. The overall framework is a sequence of steps, such as image preprocessing, partitioning of the dataset and classification based on deep learning, which constitutes a complete system for automated diagnosis of dermatological diseases with high reliability and efficiency.

.2 Data Collection

The dataset used in this study is publicly available Skin Diseases Image Dataset from the Kaggle. The dataset can be used in developing deep learning computer-aided diagnosis (CAD) systems for skin disease classification. The images used in this work have been derived from real images of the skin obtained from the open medical resources and sorted into labeled classes, appropriately prepared for supervised learning [20]. There are images of different types of skin conditions in the dataset: Eczema, Melanoma, Atopic Dermatitis, Basal Cell Carcinoma, Melanocytic Nevi, Benign Keratosis, Psoriasis, Seborrheic Keratosis, Tinea Ringworm and Warts Molluscum. Each image is labeled with a diagnosis, and a supervised deep learning approach can be used to diagnose images. These are all images of skin diseases and are not all the same resolution, lighting or appearance, as this highlights the real-life difficulties with recognising skin disease [21]. The dataset is used as a reliable dataset for training and testing deep-learning models for skin disease classification with multiple classes Figure 1.

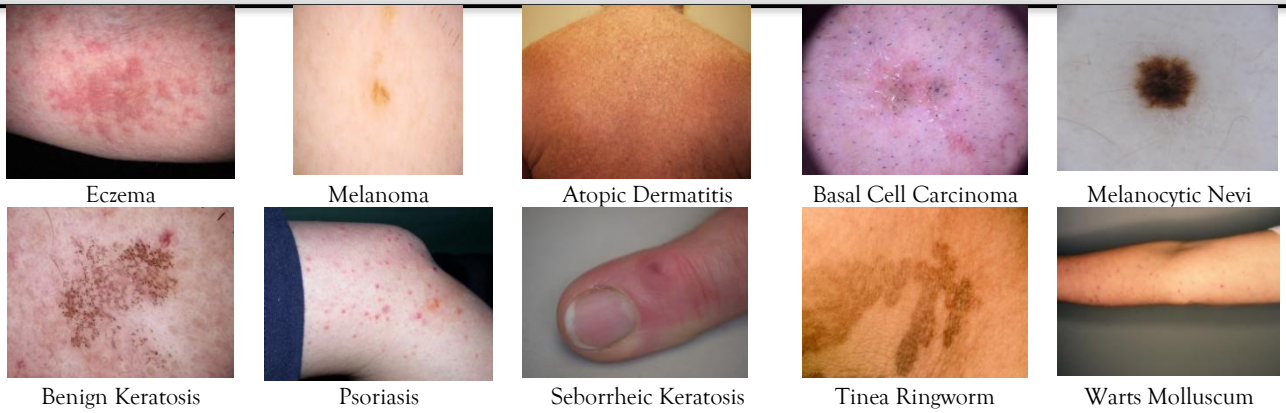

Figure 2: Skin diseases 10 classes

In this study, the balanced dataset was used, in which 10 classes contain a total of 400 images as shown in Figure 2. Furthermore, data set was further partitioned to get fair and reliable assessment of models in a train and test set [22]. The number of images used in training was 280 per class, and 120 per class for testing, with a uniform distribution of images into classes across all classes. An unbiased assessment of performance is possible through this partitioning method and a strong comparison of the performance of the different deep learning architectures can be done by using Figure 3.

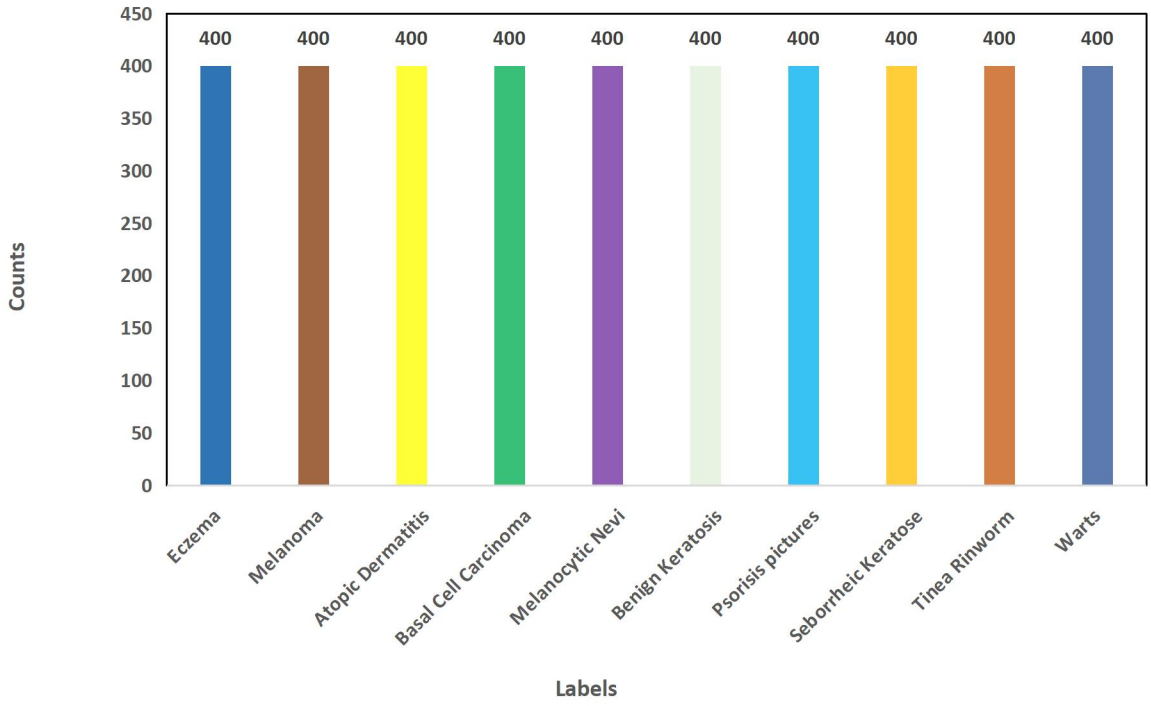

Figure 3: Distribution of each class in dataset

2.3 Data Preprocessing & Standardization

A detailed skin lesion image preprocessing which enhances the performance of deep learning-based skin cancer image classification was proposed. All images were first resized to a common size of 224 × 224 pixels for consistency and compatibility with various pre-trained CNN architectures. This will also standardize the data that is being given as input, which will simplify the complexity of the computation while training. Then it was followed

by intensity normalization, which involved scaling the pixel values to the range of 0–1. This normalisation makes the learning process stable, adds numerical consistency and accelerates the model convergence. The lighting conditions in dermoscopic images varied, therefore the images were contrasted to make them more visible and to emphasize their features. In order to further improve the image contrast, Contrast Limited Adaptive Histogram Equalization (CLAHE) was applied to emphasize the contrast level of each region and to avoid over-enhancement of small-scale details in the image of the lesions [23]. This is important especially when trying to differentiate slight variations within the same class of skin diseases. Moreover, the data sets were increased in diversity and models in generalization by means of data augmentation methods. These techniques involve random rotation, horizontal flipping, zooming and adjusting brightness to minimize overfitting and to mimic real-world variations in skin lesion appearance. In summary, the preprocessing pipeline presented here ensures high-quality input data, better feature extraction, and better classification performance of the deep learning models used for the diagnosis of skin diseases [24].

.4 Data Splitting

To make an unbiased and objective evaluation of the proposed deep learning models, the dataset was split into training and testing set. A stratified split strategy was used to ensure equal representation of all classes including Eczema, Melanoma, Atopic Dermatitis, Basal Cell Carcinoma, Melanocytic Nevi, Benign Keratosis, Psoriasis, Seborrheic Keratosis, Tinea Ringworm, and Warts/Molluscum. 280 images (70%) of each class were selected for training and 120 images (30%) were kept for testing. This led to 2800 train and 1200 test images from the total number of images, as shown in (Figure 4), respectively. The stratified division guarantees that the class distribution of both subsets is the same, so that no class imbalance bias is introduced when training and evaluating models. The training set was only utilized for fitting the parameters of the deep learning models, and the testing set was only utilized for performance evaluation. This is a good way to understand how well the models will perform on data they do not see. Therefore, the evaluation framework is useful for evaluating different architectures and the real ranking of their applicability to automated skin disease classification tasks [25].

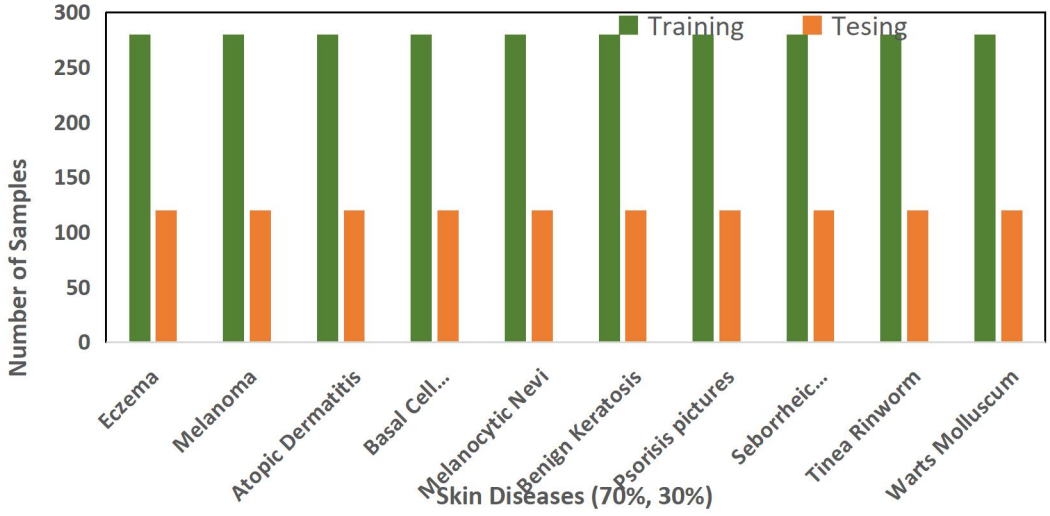

Figure 4: Samples distributions in the training and testing sets

2.5 Employed Machine Learning Models

The dermoscopic skin images were classified using multiple deep learning models into 10 categories namely Eczema, Melanoma, Atopic Dermatitis, Basal Cell Carcinoma, Melanocytic Nevi, Benign Keratosis, Psoriasis, Seborrheic Keratosis, Tinea Ringworm, and Warts/Molluscum. First a baseline CNN was developed from the scratch as a reference performance level [26]. This model was composed of several convolutional layers with ReLU activation, max-pooling layers for spatial down-sampling, and fully connected dense layers for final classification, with a softmax activation function. The baseline CNN provided the initial results, but its performance was restricted because of complexity and variability of dermoscopic images. Several advanced transfer learning models with ImageNet pre-training were used to enhance the classification performance, such as VGG16, ResNet50, InceptionV3 and MobileNetV2. The original classification layers were replaced by fully connected layers specific to the tasks in these architectures, and fine-tuned for multi-class skin disease classification. To avoid overfitting and improve the generalization ability, global average pooling layers and dropout regularization were used. The identical experimental setup was used for all models to make the results comparable. The experimental results show that all the transfer learning models outperform the baseline CNN [27]. The evaluation table shows that MobileNetV2 has the highest accuracy (92.8%), precision (92.4%), recall (92.0%) and F1-score (92.2%) among the rest. InceptionV3, ResNet50 and VGG16 also performed well with accuracy of 88.4%, 87.9% and 86.3% respectively. Overall, MobileNetV2 exhibited the best performance, owing to its lightweight design, excellent feature extraction ability, and high level of generalization, making it ideal for clinical decision support in a web-based application.

Table 1: Details of the appropriate values for the classifier's parameters with hyperparameters turning using the grid search technique

Layer Type	Parameters	Activation
Input Layer	224 × 224 × 3	-
MobileNetV2 (Base Model)	Pretrained on ImageNet + Fine-tuned last layers	ReLU
Global Average Pooling 2D	-	-
Dense	256 units	ReLU
Dropout	0.4	-
Dense	128 units	ReLU
Dropout	0.3	-
Dense (Output Layer)	10 units (Skin disease classes)	Softmax

2.6 Web-Based Deployment

A web-based deployment platform was built to enhance the proposed skin lesion classification system in a more practical manner as depicted in the system architecture. The performance of several deep learning models trained and evaluated to compare them with each other were CNN, VGG16, ResNet50, InceptionV3, and MobileNetV2. MobileNetV2 had the best performance with an accuracy of 92.80% and is thus the most suitable model to be used in the proposed system. The trained MobileNetV2 model was integrated into a web application to enable the real-time classification of skin lesion

images. The system allows its users, particularly those who are dermatologists and health professionals, to post dermoscopic or clinical skin images with a user-friendly and intuitive interface as shown in figure 5.

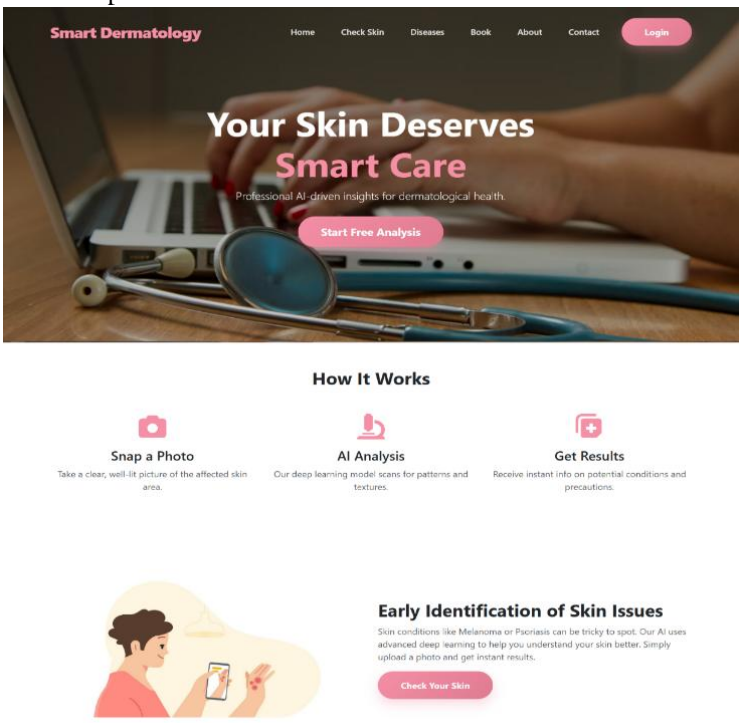

Figure 5: Home Page Interface of the Proposed Web-Based AI System

After an image has been uploaded, the same pre-processing pipeline as during model training is applied, such as resizing and normalization, as well as any other necessary image enhancement techniques that may be required for consistency and improved feature representation. Once the image is processed, it is then passed to a trained MobileNetV2 model which extracts features and classifies the image into a characterisation of the skin disease, e.g., benign or malignant lesions as the labels in the dataset suggest [28]. The decision supporting result of the prediction is presented immediately via the web interface, providing a fast, accurate and effective output of the decision supporting. The system backend is employed to load models, preprocess the coordination of the system and execute the inference, helping the deep learning model to integrate with the user interface correctly [29]. The trained model is integrated into a diagnostic support tool which can be used in real life clinical scenarios, an implementation in web. It makes it easier to use, enables real-time decision-making and illustrates the feasibility of artificial intelligence in automated skin disease detection and classification in practice as shown in Figure 6.

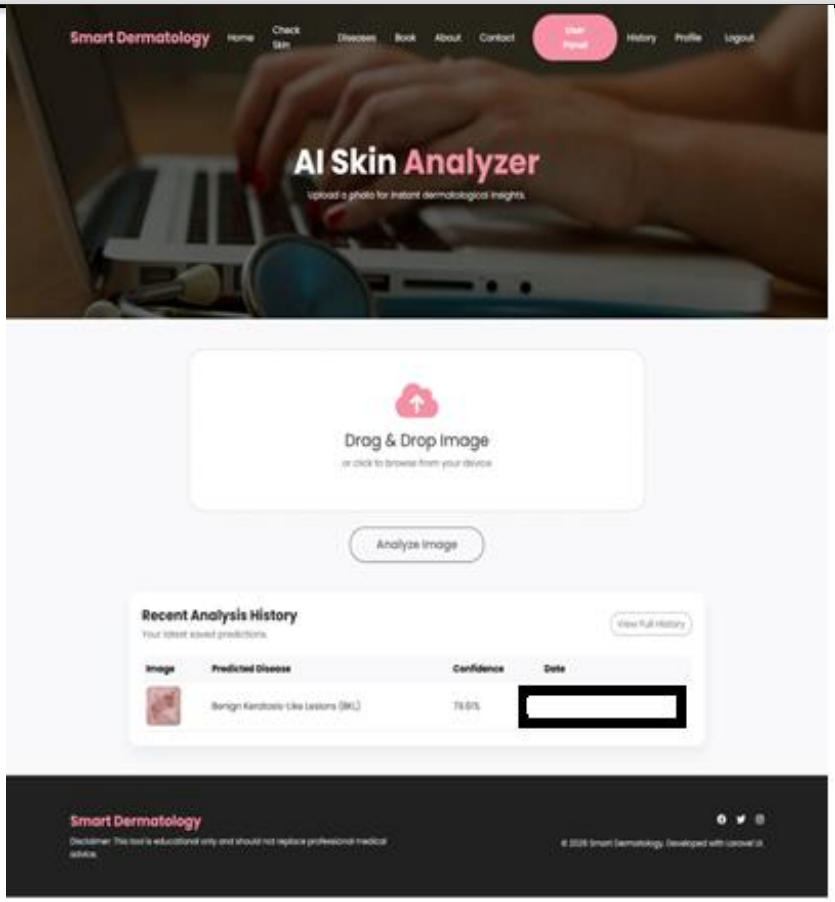

Figure 6: Clinical Decision Support Output of the Proposed AI System

3. Results and Discussion

This section summarizes the results of the experiments in the classification of skin lesions. The accuracy, precision, recall, and F1 score were used to measure the different deep learning models. This is a moderate performance of baseline CNN, as it has not been able to extract features sufficiently. Transfer learning models were able to give a very good improvement of performance. VGG16, ResNet50 and InceptionV3 gave the best feature representation. The best result was obtained with MobileNetV2. It was effective in capturing fine details of skin lesion images. In general, using transfer learning improved the accuracy and reliability of the classification. The results are in line with the use of deep learning in skin disease diagnosis.

.1 Experimental Setup

The experiments were performed on a system which consists of Intel Core i5/8700 or i7/8th generation CPUs to support the deep learning computations for skin disease classification using dermoscopic images. The system was set up to have at least 8 GB of RAM, with 16 GB recommended for efficient handling of data and smooth training of the model. To ensure quick data access and storage operations, a Solid-State Drive (SSD) with over 20GB of storage was used. All experiments were carried out on a stable and reliable operating system "Windows 10/11". Popular libraries such as TensorFlow and Keras were used to implement and test the deep learning models. In addition, the results and outputs were clearly visualized using the display resolution of 1920 × 1080. This combination of Hardware and Software enabled all the stages such

as image preprocessing, model training, model validation and testing were performed efficiently and appropriately, from which model used for automated classification of skin diseases were obtained.

4.1 Performance of Classifiers

The proposed skin lesion classification system was comprehensively assessed using a baseline CNN and the state-of-the-art transfer learning models like VGG16, ResNet50, InceptionV3 and MobileNetV2. Well known performance metrics such as accuracy, precision, recall and f1 score were used for the evaluation. All of these metrics provide a complete picture of the success rate of each model at correctly identifying images of skin lesions and in addition reveal how often they would generate false alarms and fail to pick up on an image, resulting in a false negative. The baseline CNN model achieved an accuracy of 79.10%, precision of 78.40%, recall of 77.60%, and an F1-score of 78.00%. Although CNNs represent very well the spatial information, the performance in this study is relatively low, perhaps because of the small scale of the data set used, or because the model requires prior knowledge of the data to better generalize complex patterns. This shows one of the main drawbacks to training deep learning models from scratch, particularly in medical imaging tasks where large, annotated datasets are hard to obtain.

Table 2: The result of the performance metrics corresponding with deep learning models.

Method	Accuracy	Precision	Recall	F1 Score
CNN	79.10%	78.40%	77.60%	78.00%
VGG16	86.30%	85.80%	85.00%	85.40%
ResNet50	87.90%	87.20%	86.60%	86.90%
InceptionV3	88.40%	87.80%	87.10%	87.40%
MobileNetV2	92.80%	92.40%	92.00%	92.20%

To address these challenges, transfer learning methods were used that rely on pre-trained models trained on large-scale datasets. The VGG16 model outperformed the baseline CNN model with an accuracy of 86.30%, a precision of 85.80%, a recall of 85.00%, and an F1-score of 85.40%. This can be explained by the deep architecture of VGG16, which is able to learn more hierarchical features from the images compared to a CNN.

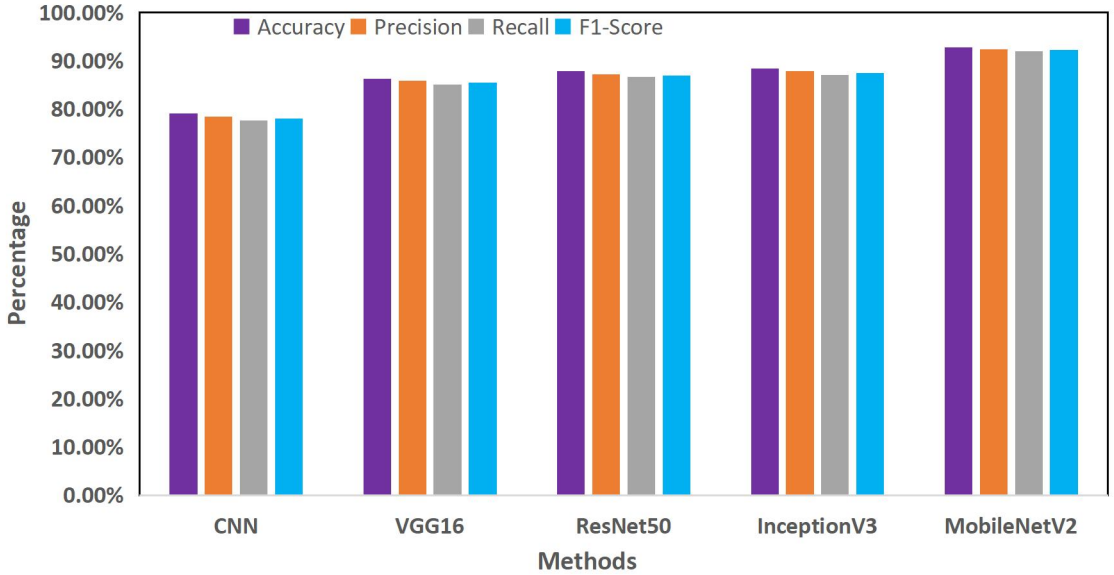

Figure 7: Visualization performance metrics of classifiers

4.2 K-Fold Cross-Validations Results

All models were evaluated using K-Fold Cross Validation to analyze the robustness and generalization of all models. This approach enables to minimize bias by testing the model on various data subsets. The baseline CNN had an accuracy of 79.10% (0.786 ± 0.007 standard deviation). It demonstrated reasonably good but non-increasing results

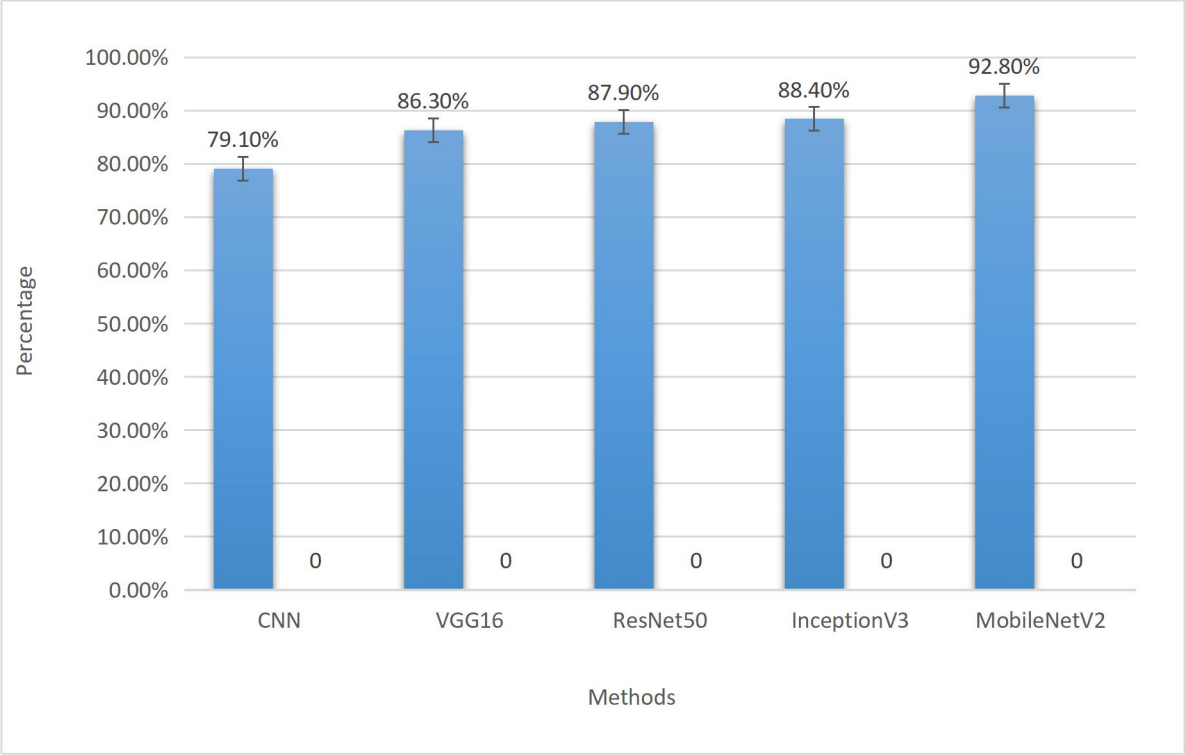

Figure 8: Cross-validation score with standard deviation bar

VGG16 achieved 86.30% accuracy with 0.859 ± 0.004 deviation. It exhibited better and steady performance. ResNet50 achieved 87.90% accuracy with 0.875 ± 0.005 deviation. It showed good and consistent learning engagement. InceptionV3 reached 88.40% accuracy with 0.881 ± 0.004 deviation. It had a reasonable level of accuracy and consistency. The accuracy of MobileNetV2 was the highest of 92.80%. It also had the lowest deviation of 0.923 ± 0.003. This means it has a good level of stability in all folds.

Table 3: Accuracy and standard deviation of different methods

Method	Accuracy	Standard Deviation (+/-)
CNN	79.10	0.786 ± 0.007
VGG16	86.30	0.859 ± 0.004
ResNet50	87.90	0.875 ± 0.005
InceptionV3	88.40	0.881 ± 0.004
MobileNetV2	92.80	0.923 ± 0.003

Overall, transfer learning models outperformed CNN. MobileNetV2 proved to be the most reliable model.

4.3 Discussion

The results obtained in this study demonstrate the effectiveness of deep learning approaches for skin lesion classification. The CNN and transfer learning models are compared, and it is seen that the accuracy, precision, recall, and F1-score of the pre-trained architectures are significantly better than the baseline CNN. The CNN model had relatively poor performance, primarily because it could not learn deep and discriminative features from the medical images, with a small training set. Transfer learning models like VGG16, ResNet50, InceptionV3, and MobileNetV2, on the other hand, exhibited significant gains. These models are trained on large-scale datasets and are able to learn more powerful and generic feature representations. Of these, the VGG16 and ResNet50 models gave a good baseline improvement, suggesting that deeper models with residual connections improve the learning ability of the complex image classification. To enhance performance, InceptionV3 introduced multi-scale feature extraction via parallel convolutional operations, which is especially beneficial in capturing nuanced variations in skin lesion patterns. In general, however, the model named MobileNetV2 had the best results, both in terms of accuracy and performance efficiency. It was designed using the insight of depthwise separable convolutions and inverted residual blocks, making it compact and making it ideal for resource limited and real-time applications such as mobile or web-based. The K-fold cross validation results also validate the reliability and generalization ability of the models. The lowest fold-wise difference was found between the folds for MobileNetV2, suggesting it performs evenly on various parts of the data. In a medical application, such as one where reliability and repeatability of predictions are paramount for clinical decision making, this stability is very important. The other important finding from this study is that the recall value was found to be significantly better with transfer learning models than the CNN model. This is especially essential for medical diagnosis, because a higher recall leads to lower risk that it will miss malignant cases. Thus, the proposed system would not only contribute to the overall accuracy but also would help to establish patient safety due to the reduction in the false negative cases. In general, the results are clear that the task of skin lesion classification is very effective in using the technique of transfer learning, particularly in the limited number of data sets. By comparing the performance of all the models, it is clear that the MobileNetV2 model is the most appropriate to be deployed in practical applications of diagnostic systems in the real world. It has high accuracy, stability, and efficiency; thus, it is considered as a promising tool for inclusion in clinical decision support tools. Finally, this work proves that deep learning systems can greatly be helpful to dermatologists in early detection and classification of skin diseases. A web-based approach to integrating these models ensures enhanced access and usability, ushering in more efficient and intelligent healthcare solutions.

Conclusions

A deep learning-based skin lesion classification method based on CNN and various transfer learning models such as VGG16, ResNet50, InceptionV3, and MobileNetV2 was presented in this study. The results indicate that transfer learning can enhance the classification accuracy over baseline performance, particularly with small medical imaging datasets. Compared to all models, MobileNetV2 obtained the highest accuracy 92.80%, precision 92.40%, recall 92.00%, F1 scores 92.20%, and had stable cross validation results. It is light-weight architecture which can be used for efficient and real-time applications. The proposed system also promises to be more useful in real-world applications, as it is being developed as a web-based application that can be used to access healthcare remotely, especially in areas that are not well-served or in rural regions. This allows users and healthcare workers to upload pictures of the skin and receive instant predictions of

diagnosis without needing to rely on the advanced local infrastructure. In general, the proposed system has a good potential for being used as a clinical decision support system for early detection of skin diseases. May help to increase the accurate diagnosis, decrease human error, and aid in identification of malignant cases at an early stage. Further work will involve expanding the data set, integrating multimodal data, and deploying in a real clinical and mobile setting to further increase accessibility.

Conflict of Interest: The authors declare no conflict of interest.

Abbreviations:

AI	Artificial Intelligence
CLAHE	Contrast Limited Adaptive Histogram Equalization
CNN	Convolutional Neural Network
CAD	Computer Aided Diagnosis
DL	Deep Learning
FTC	Follicular Thyroid Carcinoma
KNN	K-nearest Neighbor
ML	Machine Learning
SSD	Solid-State Drive
SVM	Support Vector Machine
VGG16	Visual Geometry Group-16
CAD	Computer Aided Diagnosis

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