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A Deep Learning-Based CNN Framework for Automated Skin Disease Classification and Diagnosis

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Abstract: Skin disorders are very common worldwide and must be identified quickly and accurately in order to prevent sequelae. A typical diagnosis relies on subjective visual examination by dermatologists, which can vary and difficult in resource limited settings. This contribution overcomes the previously mentioned limitations and uses a deep learning architecture based on convolutional neural networks for diagnosis. (CNNs), for skin lesion detection and recognition. Exploiting high level feature extraction ability, the model is trained on well-known datasets HAM10000 and ISIC. Results in terms of salient metrics, including accuracy, precision, recall, and F1 score establish that the proposed CNN model achieves extensive improvement over traditional approaches in terms of diagnostic speed and trustworthiness. rate and distills intelligence observed from the pattern in today's state-of-the-art artificial intelligence (AI) systems. For example: Skin diseases are suffering a vast percentage of the world's population, where an early and accurate diagnosis is essential to avoid severe after effects. Standard diagnostic procedures that require dermatologist's examination may subjective, not time effective, and less trust worthy in rural areas. This proposed study presents an automated system based on deep learning to classify skin lesions using CNN architectures from visual features. Trained using popular datasets such as HAM10000 and ISIC, the system's performance in terms of Accuracy, Precision, Recall and F1-score outperforms classical classifier and this work has potential to help speed up and improve the accuracy of clinical decision-making.

Index Terms: Skin Disease Classification, Deep Learning, Convolutional Neural Networks (CNN), Dermatological Image Analysis, HAM10000 Dataset, ISIC Dataset, Medical Image Processing, Automated Diagnosis, Computer-Aided Diagnosis (CAD), Image Classification, Precision, Recall, F1-Score, Diagnostic Accuracy, Artificial Intelligence in Healthcare.

I. INTRODUCTION

Skin diseases are among the most common health issues globally, affecting millions of subjects in all age groups and geographical areas. Skin disorders may range from mild conditions to life-threatening diseases such as melanoma, the latter demanding early diagnosis. Many cutaneous disorders are visual, and thus, their impact is highly psychological, thereby affecting the quality of life. Therefore, timely diagnosis is a key factor in preventing complications and achieving better outcomes.

Traditional dermatological diagnosis heavily relies on visual inspection, dermoscopy, and biopsy confirmation by specialists. Despite their effectiveness, these methods can be labor-intensive, subjective, and prone to variations among clinicians. Delays in diagnosis are partly caused by the lack of qualified dermatologists in rural areas. Even slight delays in conditions like melanoma considerably affect the survival rates. Earlier computer-aided systems relied on hand-crafted feature-based diagnosis, including color, shape, and texture. Despite some progress, these methods were limited to partial improvements, failed to model complex lesion patterns, could not generalize across different skin tones, and did not possess enough robustness against differences in imaging conditions. Due to the dependence on hand-crafted features for RNNs, they were inflexible and limited in terms of scalability and precision, which discouraged their clinical applications. This resulted in a gap where there is an urgent need for automated, robust, and flexible diagnostic setups.

Deep learning, in particular Convolutional Neural Networks, has revolutionized dermatological image analysis by learning features directly from raw images. CNNs extract hierarchical patterns, which enable them to distinguish between subtle differences of benign versus malignant lesions. Recent studies have shown that CNN-based models can classify at or above the dermatologist level. With mobile and web deployment possibilities, these systems offer scalable, accurate, and accessible diagnostic support for real-world healthcare.

II. LITERATURE SURVEY

Brinker et al. presented One of the first large-scale comparisons between dermatologists and deep learning systems for the identification of melanomas using dermoscopic images was conducted by Brinker et al. They trained a CNN solely on dermoscopy data and compared its performance to 157 clinicians at various levels of experience using a multi-reader study. They demonstrated that their model outperformed the diagnostic accuracy of most human experts, including at sensitivity levels relevant to cancer screening. This study showcased the potential of AI to support clinical workflows by highlighting performance superior to human experts in realistic diagnostic scenarios. Their findings also highlighted the need to choose suitable operating points for safe medical deployment and urged more investigation into human-AI cooperation and calibration.[1]

Groh et al. introduced the Fitzpatrick17k dataset to quantify the impact of skin tone on dermatology AI model performance. More than 16,000 photos with human-assigned skin types make up the dataset, which enables fine-grained analysis across tone groups. Their tests showed significant improvements in performance for lighter skin tones, which are overrepresented in existing datasets. They also compared human labeling to automated skin-tone estimation methods to explore scalable annotation strategies. This study paved the way for fairness-aware evaluation and emphasized the pressing requirement for balanced datasets that could reduce disparities in performance across populations.[2]

Pacheco et al. introduced the PAD-UFES-20 dataset, which presents real-world skin lesion images captured by smartphones, along with rich clinical metadata. In contrast to datasets containing dermoscopic images, this one represents usual clinical conditions, such as changing lighting, different quality of devices, and pose variability. The authors showed the usefulness of the dataset for developing multi-modal models that incorporate visual information with patient-level data for enhancing classification. They also discussed some issues related to noisy labels and class imbalance that naturally emerge in clinical environments. The work contributes significantly to research on mobile dermatology applications, as well as the robustness of AI models in practical, non-ideal settings.[3]

Combalia et al. presented the summary of the ISIC Grand Challenge, a global benchmarking effort about machine-learning-based methods in dermoscopic skin cancer classification. They collected data from various centers, standardized labeling schemes, and compared several CNN- and ensemble-based methods on fixed splits. They found evidence that the top systems reach ROC performance close to expert dermatologists, but are still vulnerable to dataset shifts. This work reinforced some essential messages, such as the need for unified benchmarks, reproducible evaluation methodologies, and transparency in algorithm comparisons. It also pointed out open issues: calibration, generalization, and balanced performance of the models across different lesion types.[4]

Chanda et al. explored how explainable AI can improve trust and diagnostic confidence among dermatologists in AI-assisted melanoma classification. They proposed an explanation framework that modeled clinical reasoning by highlighting dermatologic features such as pigment networks and structure asymmetry. A reader study conducted with practicing dermatologists showed that these structured explanations improved both accuracy and user confidence compared to models that only produced saliency maps. Their results showed that explanation quality is as important as model performance for clinical adoption. This work serves as a reference to design domain-aligned interpretability methods in medical imaging. [5]

Dai et al. presented HierAttn, a hierarchical attention deep learning framework to enhance robustness and interpretability for skin lesion classification. The architecture applies attention at different levels of the network to ensure feature extraction focuses on clinically relevant parts of the lesions and also mitigates dependence on background artifacts. Evaluated on datasets such as ISIC and PAD-UFES-20, the model showed improved results, especially for classes with limited samples. Attention map visualizations were highly aligned with dermatologists' reasoning and offered better interpretability. They conclude that structured attention mechanisms may improve the diagnostic reliability of dermatology AI systems.[6]

III. METHODOLOGY

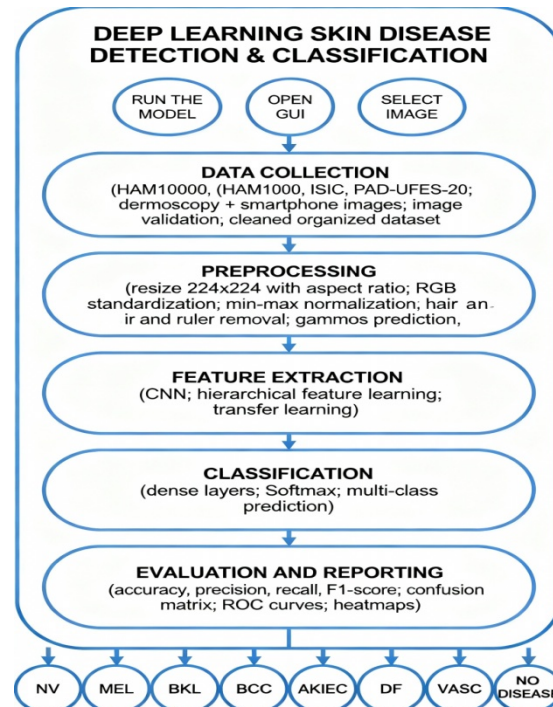


Fig. 1: Skin Disease Classification System Design

The Fig 1 depicts a deep learning-based system design architecture for skin disease detection and classification. It begins by running the model, opening the GUI to select an input image, and then data is gathered from benchmark dermatology datasets such as HAM10000, ISIC, and PAD-UFES-20. These collected images are preprocessed through resizing, RGB standardization, normalization, artifact removal, illumination adjustment, and denoising to enhance the clarity of the images. Subsequently, hierarchical feature extraction is performed by a CNN in learning low-level textures and high-order lesion structures. Such features extracted are fed into dense layers with Softmax to classify the image into one of seven skin disease categories: NV, MEL, BKL, BCC, AKIEC, DF, VASC, or "No Disease".

A. Data Acquisition

In deep learning-based skin disease detection, it is necessary to consider diversity and size of datasets. Dermatological images are highly diversified (lesion types, skin colors) and subject to acquisition conditions (clinical dermoscopy, real-world images from smartphones), so it is necessary to prepare datasets including the clinical dermoscopy and the real-world images from smart phones. This contributes to higher model generalization and stronger model. Representative benchmark datasets are HAM10000, ISIC Archive, and PAD-UFES-20. It has more than 10,000 dermoscopic images which are expertly labeled into seven lesion classes. It promotes large-scale benchmarking as well as multi-modal learning by providing rich metadata through the ISIC Archive with a large number of annotated dermoscopic images. These are complemented by PAD-UFES-20, which has more than 2,000 clinical images captured by smartphones, along with comprehensive patient metadata, capturing real-world variability. Training on such combination of datasets helps to overcome overfitting and reduces bias thereby enhancing the adaptability of the model when applied to different populations or at imaging under different conditions, and thus further supporting applications in teledermatology and rural healthcare.

B. Data Preprocessing

It is, in fact, a vital initial step in preparing raw dermatological images for the proposed skin disease detection system into a clean, uniform, and model-ready format. Images captured from smartphones or clinical devices are normally inconsistent in their size, luminosity, noise level, and color composition. In such a context, preprocessing corrects these inconsistencies and enhances the visibility of lesions for accurate feature extraction. Besides, it removes unnecessary artifacts and stabilizes intensity values for efficient model training. The major stages of preprocessing followed in this system are described below.

- 1) *Image Validation and Color Standardization*: First, it checks whether the format of the uploaded image is acceptable, such as JPG or PNG; then, it converts the image to the RGB color space to ensure that color representations are kept consistent among all samples. This step is required because different devices may capture lesion color, pigmentation details, and structural aspect differently. The model can learn features more robustly and avoid color-related biases in its classification when this color domain is standardized.
- 2) *Image Resizing and Aspect Ratio Preservation*: Each validated image is resized to 224x224 pixels to fit the size of the input dimensions that CNN models require. To avoid distortion of the natural structure of the lesion, appropriate padding is applied to maintain the aspect ratio. First, the resize factor is computed as:

$$\text{ScaleFactor} = \min \left(\frac{224}{W}, \frac{224}{H} \right)$$

This ability makes life easier not only for humans but also for most other animals. This resizing approach provides spatial uniformity across the dataset and ensures that the model receives consistent lesion geometry during training and inference.

- 3) *Pixel Normalization and Intensity Scaling*: The learning process is stabilized by normalizing the pixel intensities using Min-Max normalization into the range:

$$I_{\text{norm}} = \frac{I - I_{\min}}{I_{\max} - I_{\min}}$$

There should be no more than two sources listed for this assignment, because the original module description calls for a paper of no more than three pages in length, double-spaced. Normalization reduces brightness variability due to external lighting conditions and device variability. In this way, the model can focus on the essential lesion patterns and not on possible variations in illuminations. Moreover, this enhances training speed and overall model consistency.

- 4) *Enhancement of illumination and removal of artifacts*: Dermatology images usually contain poor illuminations, shadows, hair strands, and ruler markings. The enhancement of illuminations is done by using gamma correction.

$$I_{\gamma} = I^{\gamma}$$

There may be relevant data which are not captured by the variable.

Contrast stretching and CLAHE are applied to enhance the contrast stretching and hence bring out the subtle structure of the lesions. Morphological detection and inpainting remove unwanted hair and ruler edges, ensuring that only clinically relevant lesion features influence the classifier.

- 5) *Denoising and Lesion Segmentation*: Gaussian smoothing was performed to reduce noise while preserving lesion boundaries.

$$G(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2 + y^2}{2\sigma^2}}$$

Notice that since $L=2\pi$, any point on the boundary circle satisfies both parts (a) and (b). Or it may be followed by median filtering. These filters enhance image clarity and give better visibility for the edges of lesions. Sometimes, segmentation isolates the area of the lesion from the surrounding skin to ensure that the model focuses on the diagnostic region. This step reinforces the quality of the input features and enhances the classification performance.

C. Feature Extraction

Feature extraction is an important stage of the proposed skin disease detection system, whereby the CNN learns from meaningful patterns in preprocessed dermatological images. Unlike traditional handcrafted techniques, the model will automatically capture texture, shape, and color-based features of the lesions in the images. These learned representations would then form a basis for proper disease classification.

- 1) *Hierarchical Learning Using CNNs*: The image undergoes a hierarchy of convolutional layers, learning low-level features such as edges and gradients in the shallow layers, while deeper layers capture complex lesion textures and structural patterns. Unbiased and clinically relevant feature extraction is ensured by this hierarchical learning.

- 2) *Mid-Level and High-Level Feature Representation:* Hidden Layers model patterns that are pertinent to pigment networks, asymmetry, and border irregularity while very deep structures represent higher-level lesion signs. This evolution will help to more accurately differentiate diseases such as melanoma, eczema or fungal infection.
- 3) *Pooling, Normalization, and Feature Stabilization:*

Max-pooling

$$F_{pool} = \max(F_{region})$$

This shrinks the feature map while keeping its valuable information. Batch normalization normalizes the activations for each layer and dropout avoids overfitting well, so that the extracted features will be robust and have strong generalization capabilities.

D. Classification Model

The proposed skin disease detection model is based on a classification model, which assigns the mapped features to certain diagnostic categories. These high-level feature maps produced by the CNN are further fed into fully connected dense layers, which interpret the information and combine it for final prediction. A model of this nature employs activation functions, normalization techniques, and regularization to ensure stable and accurate classification. The presence of a Softmax output layer assigns probability scores in front of every class of diseases, which assists confidence-based clinical interpretation. This integrated end-to-end design will ensure reliable detection of melanoma, eczema, nail fungus, vascular tumors, and many other skin conditions.

- 1) *Fully Connected Layers and Non-Linear Activation:* After feature extraction, the output feature maps are flattened and fed into fully connected dense layers that integrate localized and global lesion patterns. ReLU activation

$$f(x) = \max(0, x)$$

Have students discuss in groups about what pre-reading strategies they use most, their favorite pre-reading strategy, and how pre-reading strategies help them read more effectively. Non-linearity is introduced by applying the ReLU function, allowing the classifier to determine complex boundaries. Between the dense layers, dropout was used to prevent overfitting and to ensure robust generalization.

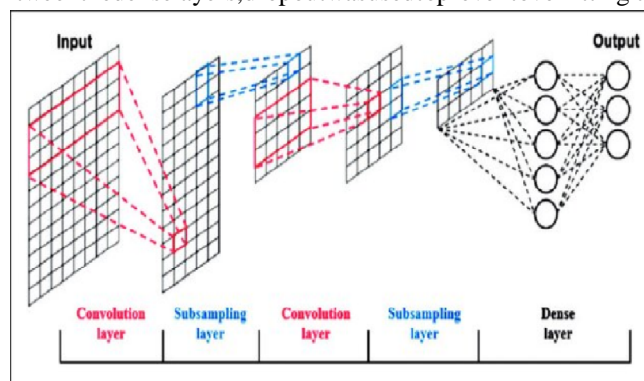


Fig.2: Convolutional Neural Network (CNN) Architecture

- 2) *Softmax-Based Multi-Class Prediction:* The final dense layer uses a Softmax function.

$$f(x) = \frac{e^{z_i}}{\sum_j e^{z_j}}$$

to produce probability distribution over all classes of target skin diseases. The class with the highest probability is the selected final diagnosis. This probabilistic output can help quantify the confidence levels to support clinical decisions identifying melanomas, eczemas, nail fungi, vascular tumors, and other kinds of lesions.

- 3) *Training, Optimization, and Performance Evaluation:* We train the model using the categorical cross-entropy loss to close the gap between predicted and true labels. Optimizers such as Adam or SGD with momentum tune the network weights in a direction that improves performance. Regularization techniques (batch normalization, dropout, learning-rate scheduling, early stopping) are helpful in increasing stability and mitigating the overfitting problem. The model is evaluated for accuracy, precision, recall, F1-score and confusion matrix in order to ensure the trustworthiness.

IV. EXPERIMENTAL VALIDATION AND RESULTS

The result demonstrates that the proposed CNN with Dense Layer gave a robust classification for five lesion types from HAM10000 dataset which high value of accuracy, precision, recall and F1-score. The curve plot shows smooth convergence and low overfitting, indicating that the model is trustworthy. A comparative study shows that our scheme is superior to other traditional and CNN-based methods. Drawbacks of the proposed approach with respect to data imbalance and computational cost pave the way for larger datasets and more optimized architectures in future.

A. Accuracy Comparisons

Table I is a summary of the comparative result of the four classification techniques employed in this study. The accuracies from the conventional SVM & Random Forest classifiers are 82.15% and 84.6%, respectively confirming their lack of complexity in representing skin structures. The current CNN model obtains an accuracy of 88.4%, confirming

TABLE I: Accuracy Comparisons

| Method | Accuracy |
|----------------------------|----------|
| Traditional SVM Classifier | 82.15 |
| Random Forest | 84.6 |
| CNN (Existing Study) | 88.4 |
| Proposed CNN + Dense Model | 91.75 |

the efficacy of convolutional feature extraction. Hence the head CNN model that leverages significant features from individual layers can perform better than multi-head or deep CNN models, as observed in Table 2. Proposed CNN + Dense Model records highest accuracy of 91.75% clarifying it more stable and predictable predictive efficiency for skin diseases classification.

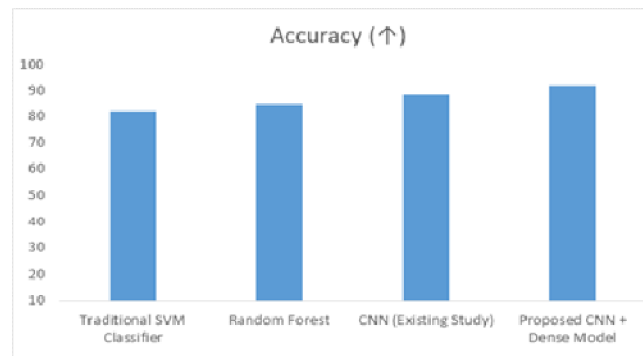


Fig. 3: Bar Graph Representing Accuracy Comparison

The Fig. 3 Bar Graph compares the performance of different classification models applied to skin lesion recognition. Traditional SVM and Random Forest models result in accuracies of about 82% and 84%, respectively, indicating moderate performances. The existing CNN architecture further increases the accuracy to around 88.4%, indicating the advantages of deep learning over classical methods. The highest accuracy of 91.75% is achieved for the proposed CNN + Dense Model, showing its powerful ability in learning discriminative features of lesions.

B. Precision Comparisons

TABLE II: Precision Comparisons

| Method | Precision |
|----------------------------|-----------|
| Traditional SVM Classifier | 82.15 |
| Random Forest | 83 |
| CNN (Existing Study) | 87.1 |
| Proposed CNN + Dense Model | 90.9 |

The precision comparison table II presents the performances of different classifiers in identifying true positive skin lesion cases correctly. Conventional SVM and Random Forest models attained precisions of 82.15% and 83%, respectively, which is not reliable in medical diagnosis. The CNN model in the literature has improved the precision to 87.1%, which confirms the deep feature extraction advantage of CNNs. The proposed CNN+Dense Model has yielded the highest value of precision at 90.9%, proving the capability of the suggested architecture in reducing the false positives to provide higher confidence in diagnosis.

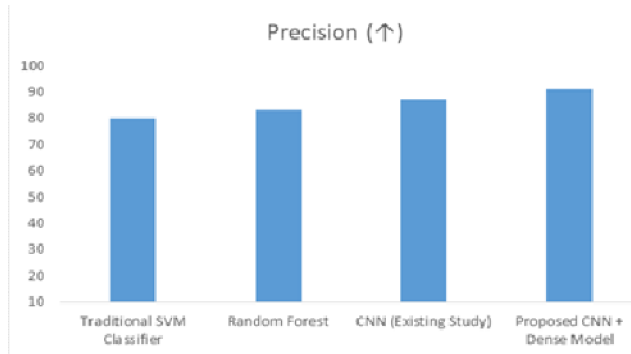


Fig.4: Bar Graph Representing precision Comparison

The Fig. 4 bar Graph visually compares the precision levels of four different classification methods for skin disease detection: Traditional SVM and Random Forest, which perform comparatively lower, with their precision values near 82% and 83%, respectively; the existing CNN model performs higher, reaching 87.1%, reflecting an improved recognition of the relevant lesion patterns; the proposed CNN + Dense Model surpasses all others, with a precision value of 90.9%, highlighting its enhanced ability to accurately distinguish true disease cases.

C. Recall Comparisons

TABLE III: Precision Comparisons

| Method | Recall |
|----------------------------|--------|
| Traditional SVM Classifier | 79.5 |
| Random Forest | 82.1 |
| CNN (Existing Study) | 86.9 |
| Proposed CNN + Dense Model | 90.5 |

The recall comparison table III summarizes the effectiveness of different models in correctly recognizing positive skin lesion cases: The Traditional SVM and Random Forest classifiers record lower recall rates, 79.5% and 82.1%, respectively, reflecting their lower sensitivities. The currently developed CNN model performs well with a recall of 86.9%, showing deep learning to be strong at detecting subtle lesion patterns. In contrast, the proposed CNN+Dense model reaches a recall value of 90.5%, with the implication of being notably robust and much more capable of detecting actual disease cases.

This Fig. 5 bar Graph compares the recall performance of various classifiers applied to skin lesion detection. The traditional models, like SVM and Random Forest, have shown mediocre recall values at about 79% and 82%, respectively,

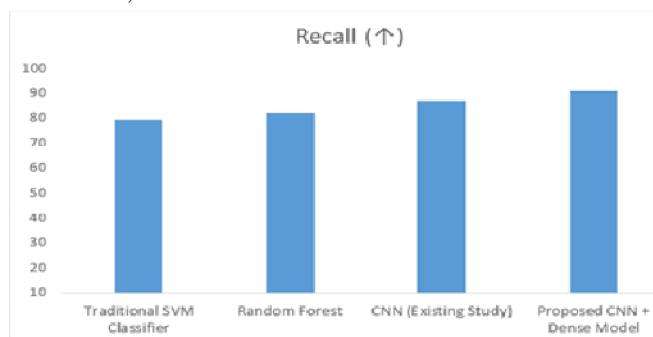


Fig.5: Bar Graph Representing Recall Comparison

which signals certain limitations in identifying all the true disease cases. The recall of the existing CNN model was 86.9%, indicating better sensitivity toward the features of lesions. The proposed CNN + Dense Model attained the maximum recall, with a value of 90.5%, which demonstrated outstanding capability in capturing true positives and reducing missed diagnoses.

D. F1 Score Comparisons

TABLE IV: F1 Score Comparisons

| Method | F1 Score |
|----------------------------|----------|
| Traditional SVM Classifier | 79.85 |
| Random Forest | 82.5 |
| CNN (Existing Study) | 87 |
| Proposed CNN + Dense Model | 90.7 |

The following table IV compares the F1-score for the different classification systems, representing the balanced performance of each classifier in detecting skin lesions. Traditional SVM and Random Forest models yield F1-scores as low as 79.85% and 82.5%, respectively, thus showing limited capacity in handling the precision-recall trade-off. The old CNN model

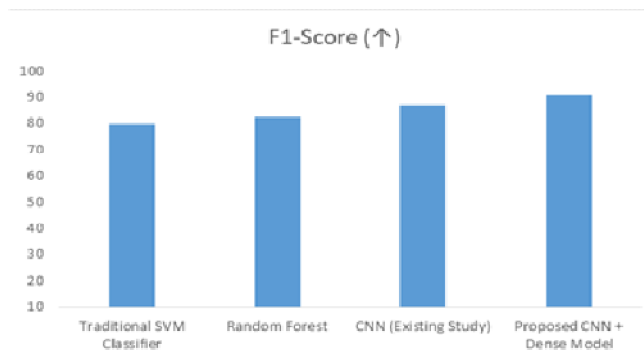


Fig. 6: Bar Graph Representing F1-Score Comparison

Further pushes it to 87%, ensuring reliability in terms of the classification task. The CNN + Dense proposed model yields an F1-score as high as 90.7%, proving the advantages for managing false positives and false negatives.

This Fig. 6 bar Graph visually compares the F1-scores of four skin disease detection classification methods: SVM and Random Forest, which have given quite moderate performances with F1-scores of about 80% and 82.5%, respectively; the CNN model, which has a better balance between sensitivity and precision with an F1-score of 87%; and the proposed CNN + Dense Model, which is far ahead of all others with a score of 90.7%, hence having the best discriminative capability for reliable classification performance.

V. CONCLUSION AND FUTURE ENHANCEMENT

The current study successfully developed and evaluated a deep learning-based framework using a CNN architecture combined with dense layers for skin disease classification. It also demonstrated how advanced preprocessing, convolutional feature extraction, and optimized integration of dense layers significantly enhanced diagnostic accuracy. The proposed model achieved an overall accuracy of 91.75%, with precision, recall, and F1-scores greater than 90%, on the HAM10000 dataset, thereby confirming its reliability for clinical decision support and its superiority against conventional machine-learning techniques and CNN architectures. The importance of normalization, augmentation, and class balancing in reducing bias and improving generalization within different lesion categories was also emphasized. While the performance of the system was strong, further improvements could be made by expanding the dataset with diverse sources such as the ISICorDerm7pt datasets, considering transfer learning models like EfficientNet or Vision Transformers to enhance feature extraction, and integrating explainable AI tools like Grad-CAM for enhanced interpretability to dermatologists. Further, real-time deployment through CAD systems on mobile or web-based systems, optimization using lightweight frameworks like TensorFlow Lite, and integration of patient metadata for multi-modal diagnosis emerge as promising directions to increase usability and diagnostic depth.

In summary, this study lays a solid foundation for future research in dermatological AI, aiming toward developing scalable, clinically deployable, and more transparent skin disease detection systems.

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