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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 examina- tion 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 datasetsHAM10000andISIC.Resultsintermsofsalientmetrics, including accuracy, precision, recall, and F1 score establish that the proposed CNN model achieves extensive improvement over traditionalapproachesintermsofdiagnosticspeedandtrustwor- thiness.rate and distills intelligence observed from the pattern in today'sstate-of-the-artartificialintelligence(AI)systems.Forex- ample:Skindiseasesaresufferingavastpercentageoftheworld'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 classifyskinlesionsusingCNNarchitecturesfromvisualfeatures. Trained using popular datasets such as HAM10000 and ISIC,thesystem'sperformanceintermsofAccuracy,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 DiseaseClassification, DeepLearning,Con- volutionalNeuralNetworks(CNN),DermatologicalImageAnaly-sis,HAM10000Dataset,ISICDataset,MedicalImageProcessing, 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,affectingmillionsofsubjectsinallagegroupsand geographicalareas. Skindisordersmayrangefrommildcondi- tions 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 vi- sual inspection, dermoscopy, and biopsy confirmation by spe- cialists. Despite their effectiveness, these methods can be labor-intensive, subjective, and prone to variations among clinicians.Delaysindiagnosisarepartlycausedbythe 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,includingcolor,shape,andtex- ture.Despite some progress,these methods were limited to partial improvements, failed to model complex lesion pat- terns,could not generalize across different skin tones,and did not possess enough robustness against differences in imaging conditions.Duetothedependenceonhand-craftedfeaturesfor RNNs,they were unflexible and limited in terms of scalabil-ity and precision, which discouraged their clinical applica- tions.Thisresultedinagapwherethereisanurgentneed for automated,robust,and flexible diagnostic sets-ups.

Deeplearning,inparticularConvolutionalNeuralNetworks, 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 thedermatologistlevel.Withmobileandwebdeploymentpos- sibilities,thesesystemsofferscalable,accurate,andaccessible diagnostic support for real-world healthcare.

II. LITERATURE SURVEY

Brinker et al. presented One of the first large-scale com- parisons between dermatologists and deep learning systemsfor the identification of melanomas using dermoscopic im- ages 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- readerstudy. Theydemonstratedthattheirmodeloutperformed thediagnosticaccuracyofmosthumanexperts,including at sensitivity levels relevant to cancer screening. This study showcasedthepotentialofAItosupportclinicalworkflowsby highlightingperformance superiortohumanexpertsinrealistic diagnostic scenarios. Their findings also highlighted the need to choose suitable operating points for safe medical deploy- mentandurgedmoreinvestigationintohuman-AIcooperation and calibration.[1]

Groh et al. introduced the Fitzpatrick17k dataset to quan- tify the impact of skin tone on dermatology AI model per- formance. More than 16,000 photos with human-assignedskin types make up the dataset, which enables fine-grained analysis across tone groups. Their tests showed significant improvements in performance for lighter skin tones, whichare overrepresented in existing datasets. They also compared human labeling to automated skin-tone estimation methods to explore scalable annotation strategies. This study paved the wayforfairness-awareevaluationandemphasizedthepressing requirementforbalanceddatasets thatcouldreducedisparities in performance across populations.[2]

Pacheco et al. introduced the PAD-UFES-20 dataset, which presents real-world skin lesion images captured by smart- phones, 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 natu- rally 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 classifi- cation. They collected data from various centers, standardized labeling schemes, and compared several CNN-and ensemble- basedmethodsonfixedsplits.Theyfoundevidencethat the top systems reach ROC performance close to expert dermatologists, but are still vulnerable to dataset shifts. This work reinforced someessential messages, such as the need for unified benchmarks, reproducible evaluation methodologies, and transparency in algorithm comparisons. It also pointedout open issues: calibration, generalization, and balanced per- formance 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 explana- tionframeworkthatmodeledclinicalreasoningbyhighlighting dermatologic features such as pigment networks and structure asymmetry. A reader study conducted with practicing derma- tologists showed that these structured explanations improved both accuracy and user confidence compared to models that only produced saliency maps. Their results showed that ex- planation 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 forskinlesionclassification.Thearchitectureappliesattention 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 derma- tologists' reasoning and offered better interpretability. They conclude that structured attention mechanisms may improve the diagnostic reliability of dermatology AI systems.[6]

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III. METHODOLOGY

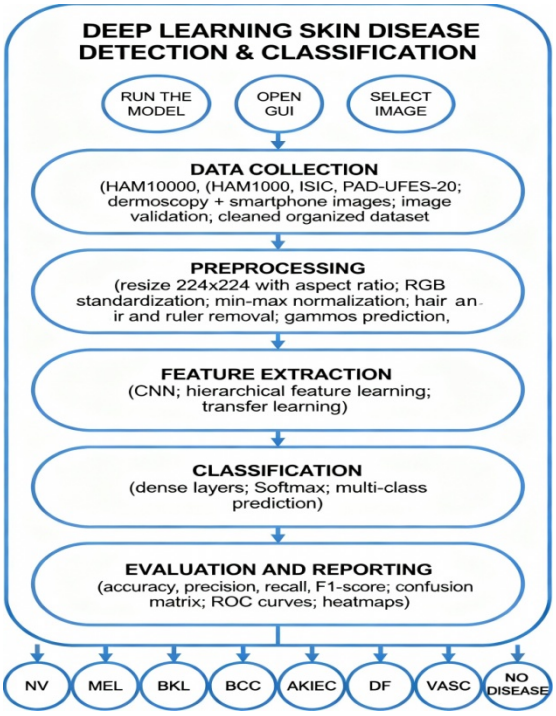

Fig.1:SkinDiseaseClassificationSystemDesign

The Fig 1 depicts a deep learning-based system design architecture for skin disease detection and classification. It beginsbyrunningthemodel,openingtheGUItoselectan 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,RGBstandardization,normalization,artifactremoval, 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-orderlesionstructures.Suchfeaturesextractedarefedintodenselayerswith Softmaxtoclassifytheimageintooneof sevenskindiseasecategories:NV,MEL,BKL,BCC,AKIEC, DF, VASC, or ”No Disease.

A. Data Acquisition

Indeeplearningbasedskindiseasedetection,itisnecessary to consider diversity and size of datasets. Dermatological images are highly diversed (lesion types, skin colors) and subject to acquisition conditions (clinical dermoscopy, real-worldimagesfromsmartphones),soitisnecessarytoprepare datasets including the clinical dermoscopy and the real-world images from smart phones. This contributes to higher model generalization:andstrongermodel.Representativebenchmark datasetsareHAM10000,ISICArchive,andPAD-UFES-20.It has more than 10,000dermoscopic 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 Archivet with a large number of annotated dermoscopic images. These are complementedbyPAD-UFES-20,whichhasmorethan2,000clinicalimages 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. DataPreprocessing

Itis,infact,avitalinitialstepinpreparingrawdermatolog- icalimagesfortheproposedskindiseasedetectionsysteminto a clean, uniform, and model-ready format. Images captured fromsmartphonesorclinicaldevicesarenormallyinconsistent in their size, luminosity, noise level,andcolorcomposition.Insuchacontext,preprocessingcorrectstheseinconsistenciesandenhancesthevisibilityoflesionsforaccuratefea ture extraction.Besides, itremovesunnecessary artifactsandsta- bilizes 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 accept- able, such as JPG or PNG; then, it converts the image to the RGB color space to ensure that color representations are kept consistentamongallsamples.Thisstepisrequiredbecause different devices may capture lesion color, pigmentation de- tails, 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) *ImageResizingandAspectRatioPreservation:* Each validatedimageisresizedto224×224pixelstofitthesize of the input dimensions that CNN models require. To avoid distortion of the natural structure of the lesion, appropriate paddingisappliedtomaintaintheaspectratio.First,theresize factor is computed as:

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

Thisabilitymakeslifeeasiernotonlyforhumansbutalso formostotheranimals.Thisresizingapproachprovidesspatial uniformity across the dataset and ensures that the model receives consistent lesion geometry during training and infer- ence.

3) *PixelNormalizationandIntensityScaling:*Thelearn-ing process is stabilized by normalizing the pixel intensities using Min–Max normalization into the range:

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

Thereshouldbenomorethantwosourceslistedforthis assignment, because the original module description calls fora paper of no more than three pages in length, double-spaced. Normalization reduces brightness variability due to external lightingconditionsanddevicevariability.Inthisway,the modelcanfocusontheessentiallesionpatternsandnoton possiblevariationsinilluminations.Moreover,thisenhances trainingspeedandoverallmodelconsistency.

4) *Enhancementofilluminationandremovalofartifacts:* Dermatologyimagesusuallycontainpoorilluminations,shad- ows, 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 contraststretchingandhencebringoutthesubtlestructure ofthelesions.Morphological detectionandinpaintingremove unwanted hair and ruler edges, ensuring that only clinically relevant lesion features influence the classifier.

5) *DenoisingandLesionSegmentation:Gaussiansmooth*-ing 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=2π, 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, segmen- tation isolates the area of the lesion from the surrounding skin toensurethatthemodelfocusesonthediagnosticregion.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 proposedskin disease detection system, whereby the CNN learns from meaningful patterns in preprocessed dermatological images. Unlike traditional handcrafted techniques, the model will au- tomatically capture texture, shape, and color-based features of thelesionsintheimages.Theselearnedrepresentationswould then form a basis for proper disease classification.

1) *HierarchicalLearingUsingCNNs:* Theimageunder-goesahierarchyofconvolutionallayers,learninglowlevelfea- tures 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-LevelandHigh-LevelFeatureRepresentation:* 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 willhelptomoreaccuratelydifferentiatediseasessuchas melanoma,eczemaorfungalinfection.
3) *Pooling,Normalization,andFeatureStabilization:*

Max-pooling

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

This shrinks the feature map while keeping its valuable in- formation. Batch normalization normalize the activations for each layer and dropout avoids overfitting well, so that the extractedfeatureswillberobustandhavestronggeneralization 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 activa- tion functions, normalization techniques, and regularization to ensure stable and accurate classification. The presence of a Softmax output layer assigns probability scores in front of everyclassofdiseases,whichassistsconfidence-basedclinical interpretation. This integrated end-to-end design will ensure reliable detection of melanoma, eczema, nail fungus, vascular tumors, and many other skin conditions.

1) *FullyConnectedLayersandNon-LinearActivation:* After feature extraction, the output feature maps are flattened and fed into fully connected dense layers that integrate local- ized and global lesion patterns. ReLU activation

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

Have students discuss in groups about what pre-reading strategiestheyusemost,theirfavoritepre-readingstrategy,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. Be- tweenthedenselayers,dropoutwasusedtopreventoverfitting and to ensure robust generalization.

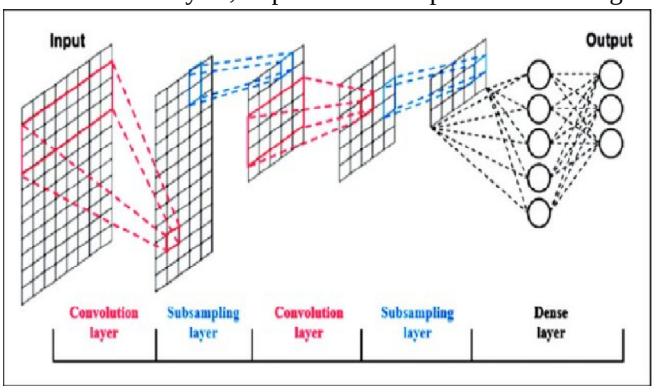

Fig.2:ConvolutionalNeuralNetwork(CNN)Architecture

2) *Softmax-BasedMulti-ClassPrediction:* Thefinaldense layer uses a Softmax function.

$$P(y_i)=\frac{e^{z_i}}{\sum_j e^{z_j}}$$

toproduceprobabilitydistributionsoverallclassesoftarget 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. Regular- izationtechniques(batchnormalization,dropout,learning-rate scheduling, early stopping) are helpful in increasing stability andmitigatingtheoverfittingproblem.Themodelisevaluated for accuracy,precision, recall, F1-score and confusion matrix in order to ensure the trustwortyness.

IV. EXPERIMENTAL VALIDATION AND RESULTS

The result demonstrates that the proposed CNN with Dense Layer gave a robust classification for five lesion types from HAM10000datasetwhichhighervalueofaccuracy,precision, recallandF1-score.Thecurveplotsshowsmoothconvergence 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 com- putational cost pave the way for larger datasets and more optimized architectures in future.

A. Accuracy Comparisons

Table.Iisasummaryofthecomparativeresultofthe 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 currentCNNmodelobtainsanaccuracyof88.4%,confirming

TABLEI: Accuracy Comparisons

Method	Accuracy
TraditionalSVMClassifier	82.15
RandomForest	84.6
CNN(ExistingStudy)	88.4
ProposedCNN+DenseModel	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.

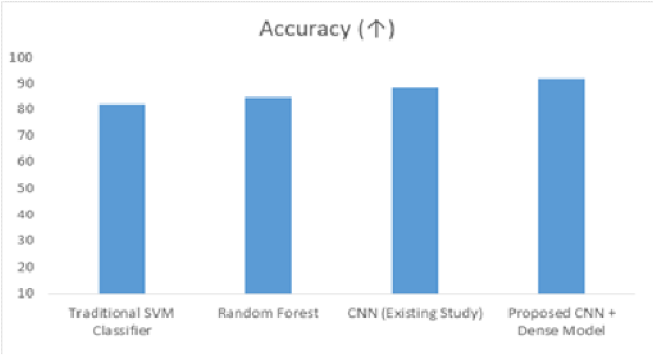

Fig.3:BarGraphRepresentingAccuracyComparison

TheFig.3BarGraphcomparestheperformanceofdifferent classification models applied to skin lesion recognition. Tra- ditional SVM and Random Forest models result in accuracies of about 82% and 84%, respectively, indicating moderate performances.TheexistingCNNarchitecturefurtherincreases the accuracy to around 88.4%, indicating the advantages of deeplearningoverclassicalmethods.Thehighestaccuracy of 91.75% is achieved for the proposed CNN + Dense Model, showingitspowerfulabilityinlearningdiscriminativefeatures of lesions.

B. PrecisionComparisons

TABLEII:PrecisionComparisons

Method	Precision
TraditionalSVMClassifier	82.15
RandomForest	83
CNN(ExistingStudy)	87.1
ProposedCNN+DenseModel	90.9

ThecomparisontableIIpresentstheperformances of different classifiers in identifying true positive skin lesion casescorrectly.ConventionalSVMandRandomForestmodelsattainedprecisionsof82.15%and83%,respectively,whichisnotreliableinmedicaldiagnosis.TheCNNmodelintheliteraturehasimprovedtheprecisionto87.1%,whichconfirms the deep feature extraction advantage of CNNs. The proposed CNN+DenseModelhasyieldedthehighestvalueofprecision at 90.9%, proving the capability of the suggested architecture in reducing the false positives to provide higher confidence in diagnosis.

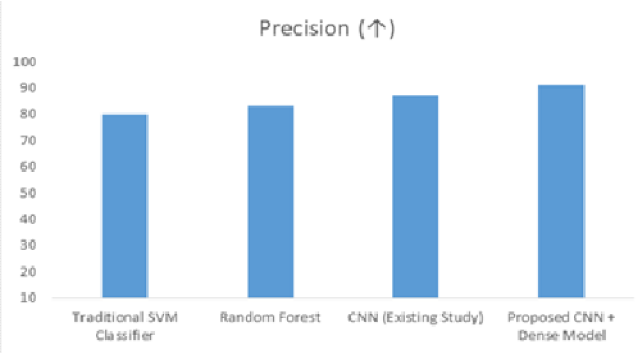

Fig.4:BarGraphRepresentingprecisionComparison

The Fig. 4 bar Graph visually compares the precision levels of four different classification methods for skin disease de- tection: Traditional SVM and Random Forest, which perform comparatively lower, with their precision values near 82%and 83%, respectively; the existing CNN model performs higher,reaching87.1%,reflectinganimprovedrecognition 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

TABLEIII:PrecisionComparisons

Method	Recall
TraditionalSVMClassifier	79.5
RandomForest	82.1
CNN(ExistingStudy)	86.9
ProposedCNN+DenseModel	90.5

TherecallcomparisontableIIIsummarizestheeffectiveness of different models in correctly recognizing positive skin lesion cases: The Traditional SVM and Random Forest classi- fiers 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.

ThisFig.5barGraphcomparestherecallperformanceof various classifiers applied to skin lesion detection. The traditionalmodels,likeSVMandRandomForest,haveshown mediocrerecallvaluesatabout79%and82%,respectively,

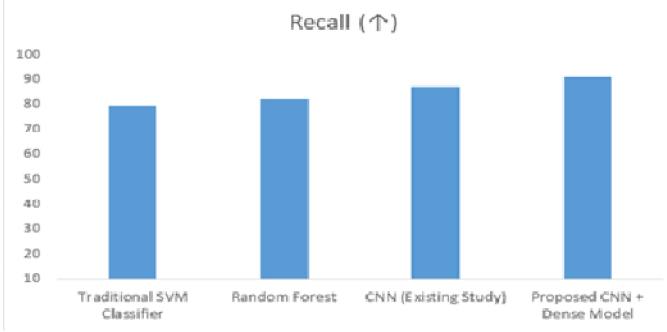

Fig.5:BarGraphRepresentingRecallComparison

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 outstandingcapabilityincapturingtruepositivesandreducing missed diagnoses.

D. F1ScoreComparisons

TABLEIV:F1ScoreComparisons

Method	F1Score
TraditionalSVMClassifier	79.85
RandomForest	82.5
CNN(ExistingStudy)	87
ProposedCNN+DenseModel	90.7

The following table IV compares the F1-score for the dif- ferentclassificationsystems,representingthebalancedperfor- mance of each classifier in detecting skin lesions. Traditional SVM and Random Forest models yield F1-scores as low as 79.85%and82.5%,respectively,thusshowinglimitedcapacity inhandlingtheprecision-recalltrade-off.TheoldCNNmodel

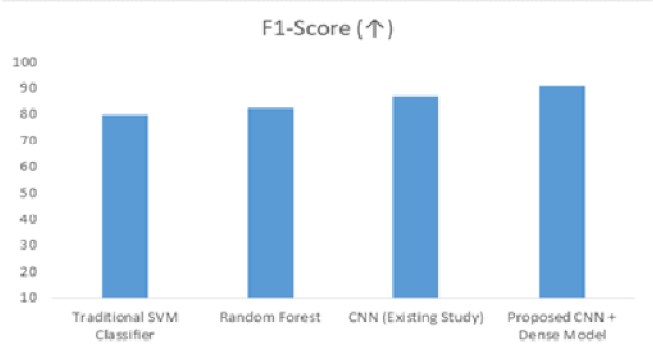

Fig.6:BarGraphRepresentingF1-ScoreComparison

Further pushes it to 87%, ensuring reliability in terms of the classificationtask.TheCNN+Denseproposedmodelyields 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 perfor- manceswithF1-scoresofabout80%and82.5%,respectively; theCNNmodel,whichhasabetterbalancebetweensensitivity andprecisionwithanF1-scoreof87%;andtheproposed CNN + Dense Model, which is far ahead of all others with a scoreof 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 combinedwithdenselayersforskindiseaseclassification. It also demonstrated how advanced preprocessing, convolu- tional feature extraction, and optimized integration of dense layerssignificantlyenhancediagnosticaccuracy.Theproposed modelachievedanoverallaccuracyof91.75%,withprecision, 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 importanceof normalization, augmentation, and class balancing in reduc- ing bias and improving generalization within different lesion categories was also emphasized. While the performance ofthe system was strong, further improvements could be made by expanding the dataset with diverse sources such as theISICorDerm7ptdatasets,consideringtransferlearningmodels like EfficientNet or Vision Transformers to enhance feature extraction, and integrating explainable AI tools like Grad- CAM for enhanced interpretability to dermatologists. Further, real-timedeploymentthroughCADsystemsonmobileorweb- basedsystems,optimizationusinglightweightframeworkslike TensorFlowLite,andintegrationofpatientmetadataformulti- modal diagnosis emerge as promising directions to increase usabilityanddiagnosticdepth.

Insummary,thisstudylays 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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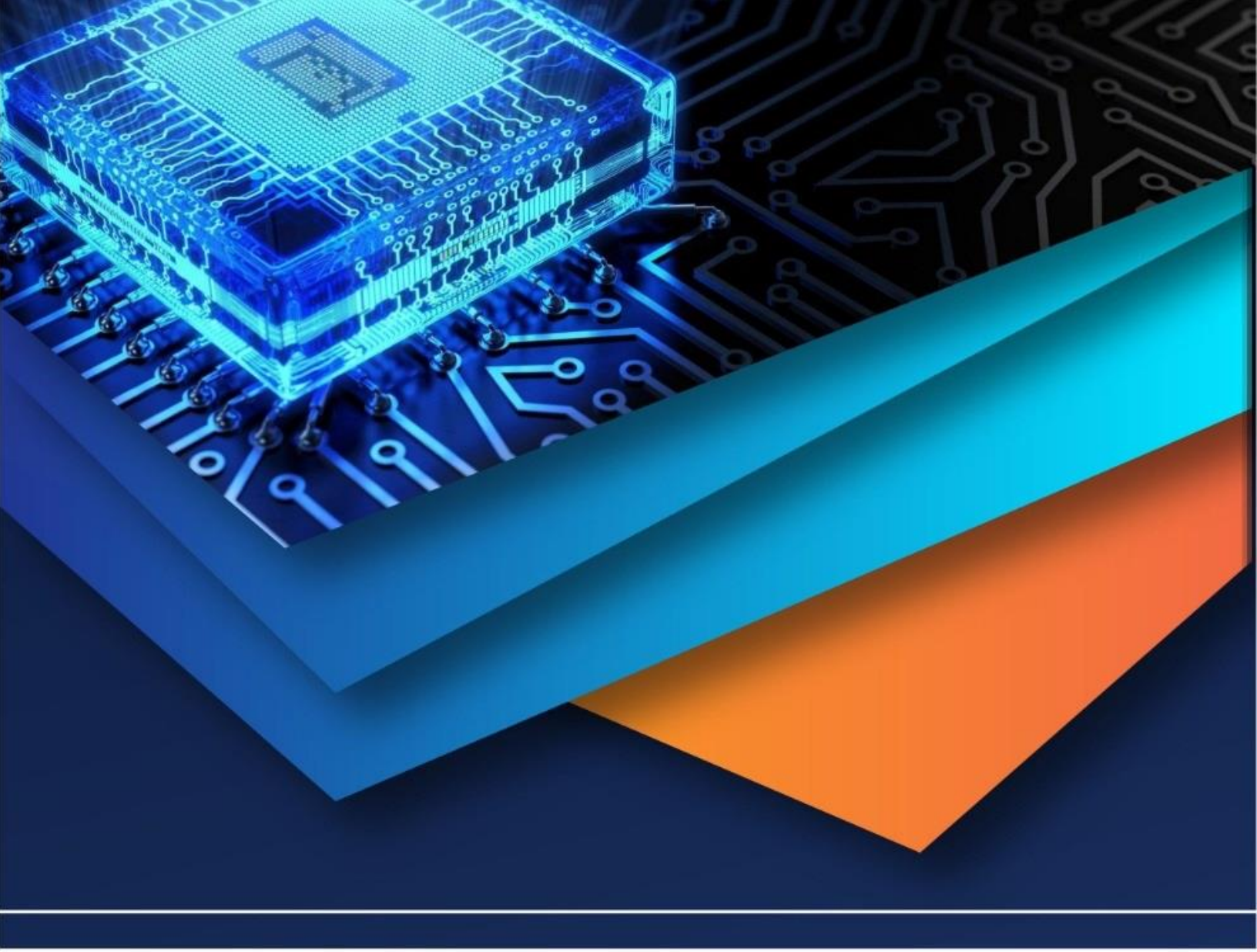

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