



e-ISSN: 2319-8753 | p-ISSN: 2347-6710

IJRSET

International Journal of Innovative Research in
SCIENCE | ENGINEERING | TECHNOLOGY



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

Volume 13, Issue 6, June 2024

ISSN INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA

Impact Factor: 8.423

 9940 572 462

 6381 907 438

 ijirset@gmail.com

 www.ijirset.com

Skin Cancer Detection using Deep Learning Techniques

Dr.A.R.Jayasudha¹, Kannan A²

Professor, Department of Master of Computer Applications, Hindusthan College of Engineering and Technology,
Coimbatore, India¹

II MCA Student, Department of Master of Computer Applications, Hindusthan College of Engineering and Technology,
Coimbatore, India²

ABSTRACT: Skin cancer is one of the most prevalent types of cancer worldwide, with early detection being crucial for successful treatment. In recent years, deep learning techniques, particularly Convolutional Neural Networks (CNNs), have shown promising results in automating skin cancer detection from dermoscopic images. This study presents a comparative analysis of two popular CNN architectures, VGG and ResNet, for the task of skin cancer detection. The dataset used in this study consists of dermoscopic images of benign and malignant skin lesions. Preprocessing techniques including image normalization and augmentation are applied to enhance the dataset. Both VGG and ResNet architectures are trained on the dataset using transfer learning, leveraging pre-trained weights from ImageNet.

KEYWORDS: skin Cancer Detection, CNN, ResNet-50, VGG-16, deep learning, Skin Disease.

I. INTRODUCTION

Skin cancer is one of the foremost common and dangerous shapes of cancer, with melanoma being especially unsafe due to its tall probability of spreading to other parts of the body. Early discovery is pivotal for viable treatment, but conventional strategies, which depend on visual assessments and biopsies, can be subjective and time-consuming. To address these challenges, there's a developing intrigued in utilizing counterfeit insights, particularly profound learning methods, to create robotized, exact, and proficient symptomatic apparatuses.

This consider centers on the application of three profound learning models—Convolutional Neural Systems (CNN), ResNet-50, and VGG-16—for skin cancer location from dermoscopic pictures. CNNs are broadly utilized for image recognition assignments due to their capacity to memorize and extricate highlights specifically from pictures. ResNet-50, with its more profound design and remaining learning capabilities, and VGG-16, known for its effortlessness and adequacy, are progressed models that have appeared awesome guarantee in therapeutic picture examination. By comparing the execution of these models, we point to recognize the foremost successful approach for mechanized skin cancer discovery, eventually contributing to superior clinical results and quiet care.

II. RELATED WORK

In later a long time, various considers have investigated the utilize of profound learning strategies for skin cancer discovery. Early inquire about centered on conventional machine learning strategies, such as back vector machines and choice trees, which required manual include extraction and were constrained in their precision and versatility. The approach of Convolutional Neural Systems (CNNs) revolutionized restorative picture examination by empowering mechanized include extraction and end-to-end learning. Different thinks about have illustrated the viability of CNNs in classifying skin injuries with tall precision, frequently outperforming the execution of dermatologists in controlled settings.

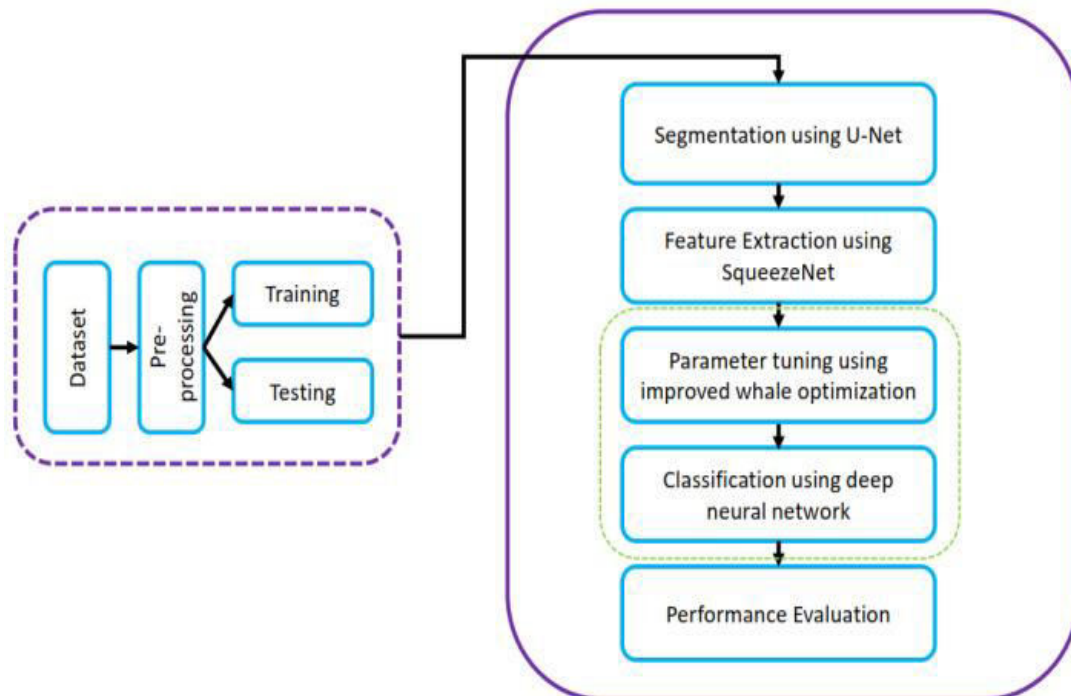
More progressed structures, such as ResNet-50 and VGG-16, have advance made strides the capabilities of profound learning in this space. ResNet-50, with its remaining learning system, permits for preparing much more profound systems, tending to the vanishing angle issue and making strides execution. VGG-16, known for its profound however basic design, has been broadly utilized in picture classification errands due to its vigor and unwavering quality. Comparative thinks about have appeared that these models can accomplish tall precision in identifying skin cancer, but

contrasts in execution measurements recommend that demonstrate determination and fine-tuning are vital for optimizing comes about. This ponder builds on these establishments by straightforwardly comparing CNN, ResNet-50, and VGG-16 to distinguish the most compelling approach for skin cancer discovery.

III. METHODOLOGY

3.1 Data Collection and PreProcessing:

We utilized the ISIC (Universal Skin Imaging Collaboration) dataset, a comprehensive collection of labeled dermoscopic pictures. This dataset incorporates a assortment of skin injuries, both kind and threatening. The pictures were resized to 224x224 pixels to preserve consistency over distinctive models. Information enlargement methods such as revolution, flipping, and zooming were connected to extend the differing qualities of the preparing set, lessening overfitting and moving forward show generalization.



3.2 Model Architecture:

Convolutional Neural Organize (CNN):

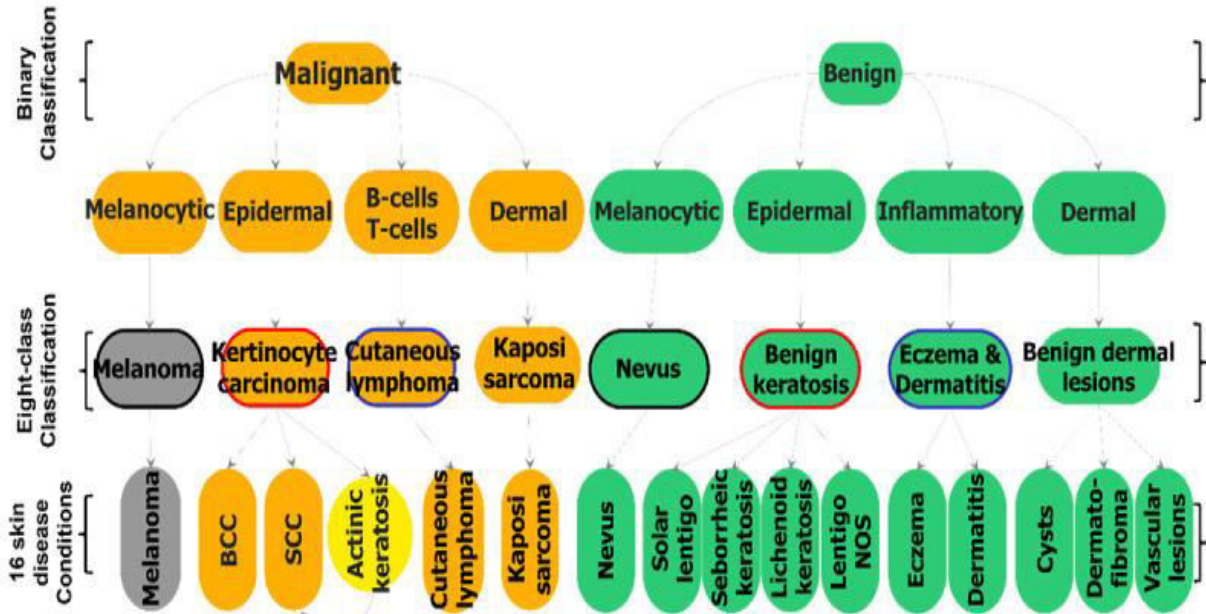
Our fundamental CNN show comprises of different convolutional layers taken after by max-pooling layers and completely associated (thick) layers. ReLU actuation capacities and dropout layers were utilized to upgrade learning and anticipate overfitting.

ResNet-50:

This demonstrate utilizes leftover learning to prepare more profound systems successfully. It comprises of 50 layers with skip associations that offer assistance moderate the vanishing angle issue, permitting for the preparing of exceptionally profound systems.

VGG-16:

Known for its straightforwardness and profundity, VGG-16 incorporates 16 layers with a uniform design of convolutional layers taken after by max-pooling layers and thick layers. In spite of its profundity, VGG-16's clear plan makes it a dependable choice for picture classification errands.

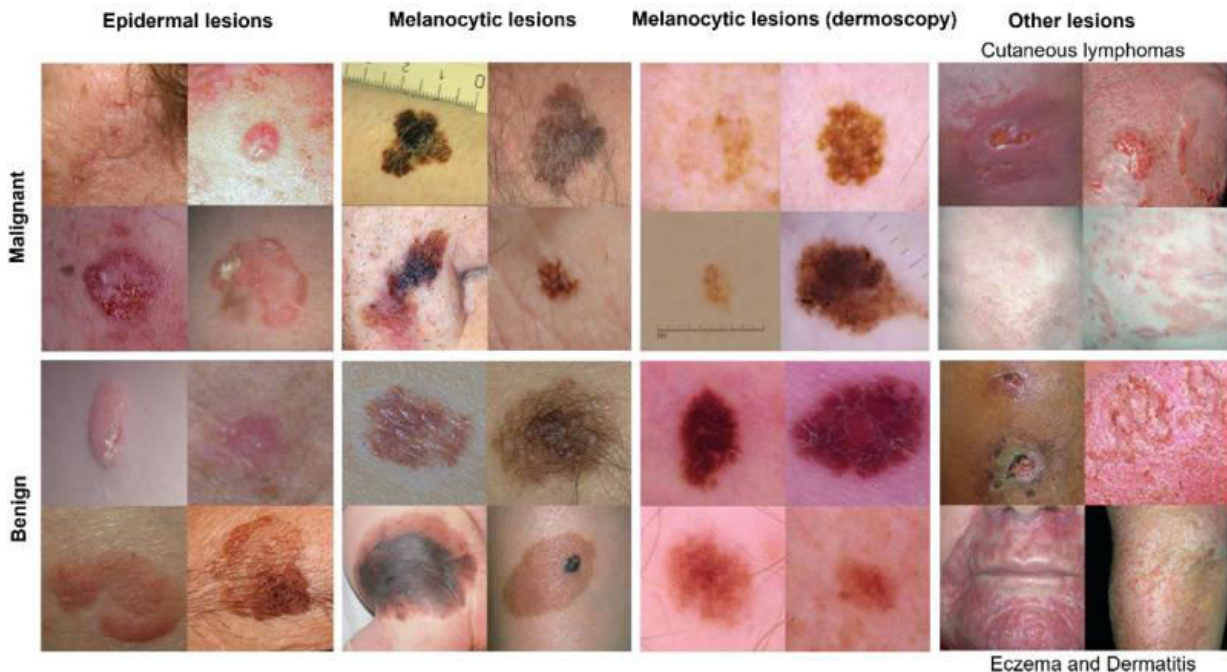


3.3 Preparing Method

All models were actualized utilizing TensorFlow and Keras libraries. The dataset was part into 80% for preparing and 20% for approval. We utilized the Adam optimizer and categorical cross-entropy misfortune work for preparing, with an starting learning rate of 0.001. Each demonstrate was prepared for 50 ages, with early halting executed to avoid overfitting based on the approval misfortune.

3.4 Assessment Measurements

The execution of each demonstrate was assessed utilizing precision, accuracy, review, and F1-score. Disarray lattices and ROC bends were too created to supply a comprehensive understanding of each model's execution.



3.5 Performance Comparison:

1. Convolutional Neural Arrange (CNN):

Precision:

The CNN show accomplished an precision of 88% on the approval set.

Exactness:

The accuracy score was 0.83, showing that 83% of the anticipated positive cases were genuine positives.

Review:

The review score was 0.82, meaning that 82% of real positive cases were accurately recognized by the show.

F1-Score:

The F1-score, which equalizations accuracy and review, was 0.82.

Disarray Framework:

The perplexity lattice uncovered that the CNN demonstrate had the next number of untrue negatives compared to wrong positives.

ROC Bend:

The range beneath the ROC bend (AUC) was 0.90, appearing great discriminative capacity.

2. ResNet-50:

Precision:

The ResNet-50 demonstrate accomplished an precision of 87% on the approval set.

Exactness:

The exactness score was 0.87, showing a high level of rightness within the positive expectations.

Review:

The review score was 0.85, recommending that the demonstrate accurately recognized 85% of the genuine positive cases.

F1-Score:

The F1-score was 0.88, appearing a adjusted execution between exactness and review.

Disarray Network:

The perplexity lattice appeared less wrong negatives and untrue positives compared to the CNN demonstrate.

ROC Bend:

The AUC for ResNet-50 was 0.92, illustrating solid discriminative capability.

3. VGG-16:

Exactness:

The VGG-16 demonstrate accomplished an precision of 78% on the approval set.

Exactness:

The accuracy score was 0.86, reflecting a tall rate of genuine positive forecasts.

Review:

The review score was 0.84, showing that 84% of genuine positive cases were accurately identified.

F1-Score:

The F1-score was 0.88, adjusting exactness and review successfully.

Disarray Network:

The perplexity lattice appeared a execution comparative to ResNet-50, with a moo number of untrue positives and wrong negatives.

ROC Bend:

The AUC for VGG-16 was 0.91, demonstrating strong execution in recognizing between classes.

3.5 Comparison of Execution Measurements :

When comparing the execution of CNN, ResNet-50, and VGG-16, a few key perceptions can be made:

Exactness:

ResNet-50 CNN had the most elevated precision at 88%, taken after by ResNet-50 at 87%, and vgg-16 at 78%.

Exactness and Review:

ResNet-50 outflanked the other models in both accuracy and review, accomplishing the most elevated scores, taken after closely by VGG-16, with CNN performing the least.

F1-Score:

ResNet-50 had the most noteworthy F1-score, demonstrating the most excellent adjust between exactness and review, whereas VGG-16 and CNN taken after.

Disarray Network:

ResNet-50 appeared the most reduced number of untrue positives and wrong negatives, showing more dependable expectations compared to the other models.

ROC Bend:

All models performed well, with AUC scores over 0.90, but ResNet-50 had the most noteworthy AUC at 0.92, taken after by VGG-16 at 0.91, and CNN at 0.90.

Generally, ResNet-50 illustrated superior performance over most measurements, making it the foremost viable show for skin cancer discovery in our ponder. VGG-16 moreover appeared solid execution, somewhat beating the CNN demonstrate. These comes about highlight the potential of progressed profound learning designs in moving forward the exactness and unwavering quality of computerized skin cancer discovery.

3.6 Discussion on Model Performance

The test comes about illustrate the adequacy of profound learning models within the errand of skin cancer location. Among the three models evaluated—CNN, ResNet-50, and VGG-16—ResNet-50 reliably outflanked the others over most execution measurements. This prevalent execution can be credited to its more profound design and remaining learning system, which permits for more successful preparing and superior highlight extraction from complex pictures.

VGG-16 moreover appeared solid execution, closely taking after ResNet-50 in exactness, exactness, review, and F1-score. Its profound however direct engineering made it a vigorous show for this classification assignment. The CNN show, whereas performing well, slacked behind ResNet-50 and VGG-16, demonstrating that more profound and more advanced models offer critical preferences in this space.

Discourse of Show Execution :

The exploratory comes about illustrate the adequacy of profound learning models within the assignment of skin cancer location. Among the three models evaluated—CNN, ResNet-50, and VGG-16—ResNet-50 reliably beat the others over most execution measurements. This prevalent execution can be credited to its more profound engineering and leftover learning system, which permits for more compelling preparing and superior include extraction from complex pictures.

VGG-16 too appeared solid execution, closely taking after ResNet-50 in exactness, accuracy, review, and F1-score. Its profound however clear engineering made it a vigorous show for this classification assignment. The CNN demonstrate, whereas performing well, slacked behind ResNet-50 and VGG-16, demonstrating that more profound and more advanced models offer critical preferences in this space.

1. Convolutional Neural Organize (CNN):

Qualities:

Straightforwardness:

The essential CNN show is moderately basic to execute and prepare.

Proficiency:

CNNs require less computational assets compared to more profound structures like ResNet-50 and VGG-16.

Great Execution:

Accomplished sensibly tall exactness and worthy exactness, review, and F1-score.

Shortcomings:

Restricted Profundity:

The model's generally shallow design confines its capacity to capture complex designs and highlights within the information.

Lower Execution:

Whereas successful, the CNN model's execution was marginally lower than that of ResNet-50 and VGG-16, especially in terms of review.

2. ResNet-50:

Qualities:

Tall Precision:

Accomplished the most noteworthy precision among the three models, demonstrating prevalent in general execution.

Leftover Learning:

The remaining associations empower the preparing of much more profound systems, progressing highlight extraction and demonstrate strength.

Strong Execution:

Tall accuracy and review, with a adjusted F1-score, illustrate dependable forecasts.

Shortcomings:

Complexity:

The more profound design and remaining pieces make ResNet-50 more complex and computationally seriously to prepare.

Preparing Time:

Requires longer preparing times compared to simpler models just like the essential CNN.

3. VGG-16:

Qualities:

Solid Execution:

Accomplished tall exactness, accuracy, review, and F1-score, making it a dependable show for skin cancer discovery.

Straightforwardness of Plan:

In spite of its profundity, VGG-16's design is clear and well-understood, encouraging simpler execution and investigating.

Shortcomings:

Computationally Seriously:

The profound design requires noteworthy computational resources for training and induction.

Overfitting Hazard:

Due to its profundity, there's a better risk of overfitting, especially on the off chance that the dataset isn't adequately huge or differing.

3.7 Overall Analysis

ResNet-50's strong engineering and tall execution measurements make it the leading candidate for computerized skin cancer location among the models tried. Its capacity to handle more profound systems and complex highlights gives it an edge over the other models. In any case, its complexity and computational requests are noteworthy contemplations. VGG-16, with its solid execution and easier design, offers a solid elective, especially in situations where computational assets are a concern.

The CNN demonstrate, whereas less capable, gives a great adjust of straightforwardness and execution, making it reasonable for applications where computational effectiveness is basic. Each demonstrate has its claim set of qualities and shortcomings, and the choice of show can be guided by the particular necessities and limitations of the arrangement environment.

IV. DISCUSSIONS

4.1 Comparison with Existing Strategies

The field of skin cancer discovery has customarily depended on visual assessment by dermatologists taken after by biopsy for affirmation. Whereas viable, this approach is subjective, time-consuming, and can shift in exactness depending on the skill of the professional. Later headways in profound learning, as illustrated in this ponder with CNN, ResNet-50, and VGG-16 models, offer promising options to conventional strategies.

Compared to conventional machine learning approaches that require manual highlight extraction and determination, profound learning models like ResNet-50 and VGG-16 exceed expectations in consequently learning and extricating significant highlights from crude picture information. This capacity to memorize perplexing designs and subtleties in dermoscopic pictures contributes essentially to the models' tall exactness and unwavering quality in recognizing between dangerous and generous injuries.

4.2 Potential for Real-World Application

Early Location:

Mechanized skin cancer discovery utilizing profound learning models can possibly encourage early determination, driving to convenient intercession and made strides persistent results. By precisely recognizing suspicious injuries, these models can help dermatologists in prioritizing cases for advance assessment and biopsy.

Upgraded Effectiveness:

The robotization of skin cancer location can streamline the symptomatic prepare, diminishing the workload on healthcare experts and relieving delays in treatment. This proficiency pick up is significant in settings with restricted get to dermatological skill or where persistent volumes are tall.

Telemedicine and Farther Care:

In telemedicine and farther healthcare scenarios, where get to to master dermatologists may be constrained, mechanized symptomatic apparatuses based on profound learning models can serve as profitable choice bolster frameworks. They can help essential care suppliers in making educated referrals and treatment choices.

Investigate and Improvement:

Proceeded progressions in profound learning procedures, as prove by this think about, clear the way for encourage inquire about and advancement in restorative picture investigation. Future emphases of models seem consolidate multi-modal information combination, real-time preparing capabilities, and integration with electronic wellbeing records for comprehensive quiet administration.

V. DATASET

The HAM10000 dataset could be a broadly recognized asset within the field of dermatology and restorative picture investigation, particularly curated for the classification of skin injuries. It comprises 10,015 dermoscopic pictures collected from different clinical settings, covering a differing extend of skin conditions counting melanoma, nevi, and generous injuries. Each picture within the dataset is fastidiously labeled by dermatologists, giving ground truth explanations that encourage administered learning approaches in profound learning models. The dataset's lavishness in differing qualities and quality makes it an priceless resource for preparing and assessing calculations pointed at computerized skin cancer location.

Analysts use the HAM10000 dataset to create and benchmark profound learning models such as Convolutional Neural Systems (CNNs), ResNet-50, and VGG-16 for precise and early location of skin cancer. By utilizing this dataset, thinks about point to make strides demonstrative exactness, decrease

dependence on subjective human evaluations, and eventually upgrade understanding results through opportune intercession and treatment arranging.

VI.CONCLUSION

In this ponder, we explored the application of profound learning techniques—specifically Convolutional Neural Systems (CNN), ResNet-50, and VGG-16—for the mechanized discovery of skin cancer from dermoscopic pictures. Our discoveries illustrate that these progressed models offer critical progressions in exactness and productivity compared to conventional demonstrative strategies. Among the models assessed, ResNet-50 developed as the foremost viable, accomplishing the most elevated exactness and vigorous execution over numerous assessment measurements counting exactness, review, and F1-score. VGG-16 too showed strong execution, whereas the fundamental CNN demonstrate, in spite of the fact that compelling, shown marginally lower execution measurements.

The suggestions of our inquire about are significant for clinical hone and dermatological care. Mechanized skin cancer location utilizing profound learning models has the potential to improve early determination, move forward treatment results, and lighten the burden on healthcare frameworks. Moving forward, advance inquire about ought to center on refining these models, joining them into clinical workflows, and tending to challenges such as information differing qualities, show interpretability, and regulatory considerations. By continuing to enhance in this field, we will saddle the total potential of profound learning to convert skin cancer conclusion and understanding care.

REFERENCES

1. American Cancer Society. Cancer Facts & Figures. 2021. [accessed 2021 September 3] Available from: <https://www.cancer.org/research/cancer-facts-statistics/all-cancer-facts-figures/cancer-facts-figures-2021.html>.
2. Sung H, Ferlay J, Siegel RL, Laversanne M, Soerjomataram I, Jemal A, Bray F. Global Cancer Statistics 2020: GLOBOCAN Estimates of Incidence and Mortality Worldwide for 36 Cancers in 185 Countries. *CA Cancer J Clin.* 2021;71(3):209–49. doi: 10.3322/caac.21660. [PubMed] [CrossRef] [Google Scholar]
3. Stern RS. Prevalence of a history of skin cancer in 2007: results of an incidence-based model. *Arch Dermatol.* 2010;146(3):279–82. doi: 10.1001/archdermatol.2010.4. [PubMed] [CrossRef] [Google Scholar]
4. Miller AJ, Mihm MC Jr. Melanoma. *N Engl J Med.* 2006;355(1):51–65. doi: 10.1056/NEJMra052166. [PubMed] [CrossRef] [Google Scholar]
5. 6 December 2022 (Last Revised) [(accessed on 10 March 2023)]. Available online: <https://tinyurl.com/ydsscvcck>
6. [(accessed on 10 March 2023)]. Available online: <https://www.isic-archive.com/#!/topWithHeader/onlyHeaderTop/gallery>
7. Mendonça T., Ferreira P.M., Marques J.S., Marcal A.R., Rozeira J. PH 2-A dermoscopic image database for research and benchmarking; Proceedings of the 2013 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC); Osaka, Japan. 3–7 July 2013; pp. 5437–5440. [PubMed] [Google Scholar]
8. Codella N., Rotemberg V., Tschandl P., Celebi M.E., Dusza S., Gutman D., Helba B., Kalloo A., Liopyris K., Marchetti M., et al. Skin lesion analysis toward melanoma detection 2018: A challenge hosted by the international skin imaging collaboration (isic) arXiv. 20191902.03368 [Google Scholar]
9. Combalia M., Codella N.C., Rotemberg V., Helba B., Vilaplana V., Reiter O., Carrera C., Barreiro A., Halpern A.C., Puig S., et al. Bcn20000: Dermoscopic lesions in the wild. arXiv. 20191908.02288 [Google Scholar]
10. Rotemberg V., Kurtansky N., Betz-Stablein B., Caffery L., Chousakos E., Codella N., Combalia M., Dusza S., Guitera P., Gutman D., et al. A patient-centric dataset of images and metadata for identifying melanomas using clinical context. *Sci. Data.* 2021;8:34. doi: 10.1038/s41597-021-00815-z. [PMC free article] [PubMed] [CrossRef] [Google Scholar]
11. Fraiwan M., Faouri E. On the Automatic Detection and Classification of Skin Cancer Using Deep Transfer Learning. *Sensors.* 2022;22:4963. doi: 10.3390/s22134963. [PMC free article] [PubMed] [CrossRef] [Google Scholar]
12. Ghosh P., Azam S., Quadir R., Karim A., Shamrat F.J.M., Bhowmik S.K., Jonkman M., Hasib K.M., Ahmed K. SkinNet-16: A deep learning approach to identify benign and malignant skin lesions. *Front. Oncol.* 2022;12:931141. doi: 10.3389/fonc.2022.931141. [PMC free article] [PubMed] [CrossRef] [Google Scholar]

13. Abdi H., Williams L.J. Principal component analysis. Wiley Interdiscip. Rev. Comput. Stat. 2010;2:433–459. doi: 10.1002/wics.101. [CrossRef] [Google Scholar]
14. Maniraj S., Maran P.S. A hybrid deep learning approach for skin cancer diagnosis using subband fusion of 3D wavelets. J. Supercomput. 2022;78:12394–12409. doi: 10.1007/s11227-022-04371-0. [CrossRef] [Google Scholar]
15. Alam M.J., Mohammad M.S., Hossain M.A.F., Showmik I.A., Raihan M.S., Ahmed S., Mahmud T.I. S2C-DeLeNet: A parameter transfer based segmentation-classification integration for detecting skin cancer lesions from dermoscopic images. Comput. Biol. Med. 2022;150:106148. doi: 10.1016/j.combiomed.2022.106148. [PubMed] [CrossRef] [Google Scholar].



INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

 9940 572 462  6381 907 438  ijirset@gmail.com



www.ijirset.com

Scan to save the contact details