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DeepSkin: A Deep Learning Approach for Skin Cancer Classification and Detection

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Abstract: One of the diseases that propagate fastest across the globe due to lack of adequate health facilities is skin cancer. Successful prevention is only possible through early and proper diagnosis; however, dermatologists often face difficulties with early diagnosis. DL has simplified the process of identifying skin cancer. CNNs are the most successful at object location and classification. In this study, the HAM10000 dataset that consists of 10,015 samples of seven types of skin lesions is employed. Preparation methods such as sampling, DullRazor to remove hair, and segmentation using an autoencoder-decoder approach enhance the quality of pictures. A number of YOLO models including YOLOv5, YOLOv6, YOLOv7, and YOLOv8 are employed to detect lesions. Some of the DL architectures that are used in categorization include ResNet150, DenseNet169, VGG16, DenseNet201 and Xception. Among them, Xception was the most accurate, indicating that it was superior in feature extraction. This research enhances the precision of diagnosing skin cancer by employing advanced detection and classification algorithms. It assists in early intervention and improved patient outcomes.

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*“**Index Terms** - Skin cancer, segmentation, deep learning, CNN, Densenet169, Resnet50, Xception, Densenet201, InceptionV3.”*

1. INTRODUCTION

A tumor develops when the healthy cells begin to change and grow uncontrollably. Tumors could be both malignant and noncancerous. Tumors may turn malignant and be transferred to other body parts [1]. An innocent tumor can occur but it usually does not spread. Skin cancer occurs when there is an abnormal development of skin cells. It is the most prevalent form of cancer nowadays and can occur in any part of the body. It is expected that more than 3.5 million cases of various forms of melanomas will be detected annually [2], [3]. This is more than all the cases of lung, bone and colon cancers combined. Actually, every 57 seconds, someone dies because of melanoma. The early detection of cancer on dermoscopy images has a high probability of survival. Therefore, pathologists will clearly improve and do more work when they are able to find skin excrescences precisely automatically. The aim of the dermoscopy process is to enable every melanoma patient to perform better. Dermoscopy is a procedure of skin imaging that is noninvasive and utilizes a magnified and brightened picture of the harmed part of the skin, making the spots more visible, which reduces the reflection of the face [4]. The importance of early detection of skin cancer remains high. It is difficult to determine whether a skin lesion is cancerous or not as they all appear the same. The sun with its harmful UV radiation and UV tanning beds are the two most common causes of skin cancer. Dermatologists particularly have a difficult time distinguishing between melanoma and non-melanoma lesions as the lesions and skin do not appear very different [5]. The main problem of similar opinion is largely dependent on personal opinion and can hardly be duplicated. Robotization and deep literacy allow the case to obtain an early opinion report, and with the help of this report, the case can discuss therapy with dermatologists [6]. Early detection of skin cancer is crucial since it has limited treatment options. To prevent skin cancer, one of the best methods is to be in a position to assess it adequately and identify it. Deep literacy has widely been adopted, even in those activities that necessitate reading and writing without supervision [7]. The most significant tools of object identification and bracket problems have become CNNs. Due to this, CNNs that are trained in an end-to-end fashion in a controlled environment eliminate the need of human operators to create feature sets manually. CNNs have been more successful in the recent years in sorting skin cancer lesions than competent human professionals.

Design a DL-based system to detect skin cancer by utilizing dermoscopy images to enhance early detection through the use of DL algorithms, such as CNNs. It is aimed at simplifying the distinction between the malignant and benign lesions, which will result in the quicker treatment and greater mortality rates. The aim of the system is to assist the pathologists by providing them with fast and precise analysis which will enhance the efficiency of the overall work with melanoma patients.

Skin cancer and especially melanoma is a significant health hazard and its prevalence is on the increase worldwide. The current problem is that it is not easy to distinguish between benign and malign tumors, which hinders their early detection and timely treatment. There is dermoscopy which is very handy, however it relies heavily on the judgment of people and thus is difficult to achieve a steady outcome. This indicates the need of an automated solution with DL technology to improve the accuracy of diagnosis, enable early intervention and address the large gap in the effectiveness of skin cancer prevention and treatment.

2. LITERATURE SURVEY

In this paper, an image processing-based approach to detecting skin cancer during its early stages will be given, with the help of an optimized CNN based on the refined whale optimization method. Relative measurements of two datasets have shown improved performance. The proposed system is more accurate in making the detection as it relies on a superior CNN and the superior whale optimization method. This demonstrates that it is more effective than other strategies. The potential issues are that the algorithm is overly complex and the optimization is resource intensive, i.e. may require a lot of computing power and time. Difficulties involve the requirement to have a substantial amount of computing power to optimize it, there is a probability of the algorithms being overly complex, and the system requires a broad spectrum of datasets to ensure its functionality on different skin types and conditions. The article suggests a possible approach to early skin cancer diagnosis, which uses an optimized CNN with an improved whale optimization algorithm, which shows superior performance compared to the rival methods, although it has restrictions associated with processing power and diversity of the data sets.The study will discuss the state of art DL algorithms in skin cancer diagnosis and classification, the use of deep convolutional neural network models to solve the problems, and the image quality concerns in dermoscopic images.

[9] This research examines cutting-edge DL methodologies for the diagnosis and classification of skin cancer, highlighting the application of deep convolutional neural network architectures to tackle problems, including image quality concerns in dermoscopic pictures. The proposed solution involves a high level of DL neural networks, particularly the convolutional architectures, to categorize skin lesions more sophisticatively. It corrects the issues of dermoscopic images generated by artifacts, noise, and shadows. Deep convolutional neural networks can be very complex and require a significant amount of computing power, which can be an issue. Also, you might have to consider how simple it is to comprehend the model and whether it might be overfitting. The restrictions include the impact of lack of quality of dermoscopic pictures to classify accurately, the potential computing resource requirements, and the need to have robust solutions to suit the various morphological features and types of skin lesions. The study provides an overall view of how deep convolutional neural networks can assist in detecting skin cancer, and it revolves around how they can be utilized to assist in addressing issues in dermoscopic images. Although promising, addressing the issues of computation and ensuring that the system is robust are essential so that it can be applicable in the real world.[14] The study presents a skin cancer classification system based on the image processing and ML.

[14] This research introduces a skin cancer classification method utilizing image processing and ML techniques. It applies contrast stretching, OTSU thresholding to divide it into segments, feature extraction (GLCM, HOG, color), PCA reduction, SMOTE sampling, and random Forest classification. It achieves 93.89% accuracy in the ISIC-ISBI 2016 data. The method is fairly precise (93.89) in the classification of skin cancer, thus early detection. It is a mixture of contrast stretching, feature selection, and Random Forest classification which is effective with dermatologists. Scalability and real-time processing of the system can become problematic, although it is rather precise. It requires a large amount of computing power, and its performance can vary based on the dataset and clinical scenario. The proposed system may not be able to handle other skin problems that are not included in the database and reliance on specific algorithms may render it less adaptable. Moreover, real implementation might require additional validation and trials. The combination of contrast stretching, feature selection and RF classification is effective in classifying skin cancer. The procedure has potential to assist physicians in the early detection of skin cancer though it requires more of testing and practical application.[6] The study is concerning the use of ML and image processing to locate and categorize skin cancer.

[6] This research is about utilizing ML and image processing to find and classify skin cancer. It applies dermoscopic image pre-processing, including hair removal and Gaussian filtering, and color-based k-means clustering to divide the image. Features are extracted using ABCD criterion and GLCM. In the ISIC 2019 Challenge dataset, MSVM is demonstrated to be 96.25% accurate. The algorithm can accurately identify the various subtypes of skin cancer 96.25% of the time. It uses a combination of sophisticated pre-processing, color-based segmentation, and powerful feature extraction to enable it to identify and classify objects earlier. Although the system might be fairly accurate, it may not be able to expand and operate with other kinds of data. It might not be effective in the real world where situations are dynamic because it relies on the pre-processing processes and classifiers. The proposed solution may fail to address any skin issues not included in the dataset used. It is founded on the concept that dermoscopic images are universal and thus its application in practice might require additional testing and modification to adapt to various clinical situations. This system employs a huge amount of pre-processing and segmentation and MSVM classification to locate and identify the skin cancer with 96.25% accuracy. Its holistic approach enhances the ability to detect at an early stage; however, to be effective it requires additional validation and adaptation to diverse clinical settings.The project is on creating a CNN model capable of detecting skin cancer using Python, Keras and Tensorflow.

[7] This project is about making a CNN model that can find skin cancer using Python, Keras, and Tensorflow. The model involves DL to classify the types of skin cancer in order to be identified at an early stage. It achieves this through a variety of network designs, which include Convolutional, Dropout, Pooling and Dense layers. Transfer Learning enhances convergence, and the data are the archives of the ISIC competition. The system

employs CNNs which are known to be more precise than any other form of neural networks as regards visual imaging activities. It is scalable and effective as it is based on Keras and Tensorflow (Python). Transfer Learning makes it easier to get things going, and experimentation with the ISIC data provides a robust means of assessment. Although the proposed method may perform effectively, it may be difficult to interpret since the models of DL are complex in nature. In addition, resource-intensive training and the risk of overfitting can occur, and thus, a high level of optimization and adjustment is required. The method may not be feasible to generalize to a large variety of skin conditions that are not represented in the ISIC data. This may be difficult to implement because of issues with interpretability, large computing requirements, and the requirement of large labeled datasets. This experiment demonstrates that CNNs may be applied to detect skin cancer and emphasizes the importance of its early detection. Models perform well when using Transfer Learning and the other forms of networks. Although this may be promising, before applying it to the real world, issues such as its ease of understanding and its correlation with the real world need to be solved.

3. METHODOLOGY

i) Proposed Work:

DL to detect and classify skin cancer is developed to enhance early detection and accuracy. The system is based on the HAM10000 data set, comprising seven categories of skin lesions. It applies preprocessing techniques such as sampling, DullRazor to remove hair and an autoencoder-decoder approach to segmentation. To detect lesions, advanced YOLO models, such as YOLOv5, YOLOv6, YOLOv7, and YOLOv8 are implemented to locate the precise locations that are affected. DL models such as ResNet150, DenseNet169, VGG16, DenseNet201, and Xception are employed in order to classify lesions. The algorithm relies on CNNs to detect and categorize objects, extracting features and identifying patterns. Automated analysis assists dermatologists in detecting issues on the skin earlier on and thus they do not need to use manual diagnosis to a large extent. The combination of the latest detection and classification models allows a more accurate and efficient diagnostic process, allowing more people to receive the treatment they need and helps patients recover better.

ii) System Architecture:

This image demonstrates how to identify and locate the skin cancer. The process begins by a Dataset Input that contains pictures of skin lesions. Image Preprocessing techniques like scaling, transformations, and segmentation are then used to process these images. The data sets are two Train and Test. We use the Train set to train models with various architectures such as ResNet50, DenseNet169, VGG16, Xception, DenseNet201 and YOLO. The Test set is used to observe the performance of the model by using such measures as Accuracy, Precision, Recall and F1-score. The objective of the technique is to idly distinguish and classify skin cancer based on provided pictures.

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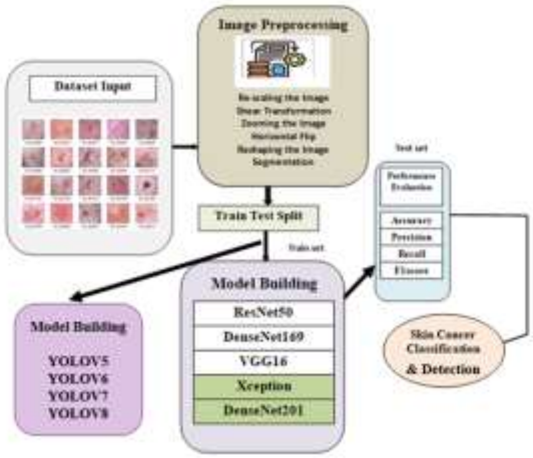

Fig 1 System Architecture

iii) Dataset Collection:

The Skin Cancer Data dataset is a re-upload of HAM10000 dataset which has been adapted to a notebooks project. This highly selected data has been highly refined to render it more useful and relevant. It contains much information on skin cancer that develops out of various types of skin lesions. The sample size of the dataset stands at 10,015, which is an excellent resource to conduct research and experiments. Processing stages involve activities such as sampling to obtain a representative sample of data and through techniques such as dull razor and autoencoder-based segmentation to achieve optimal data quality. This is a well selected dataset that can be used by researchers and practitioners in working in dermatology. It is a systematized and refined compilation that aids individuals to acquire greater insight into skin cancer detection and classification.

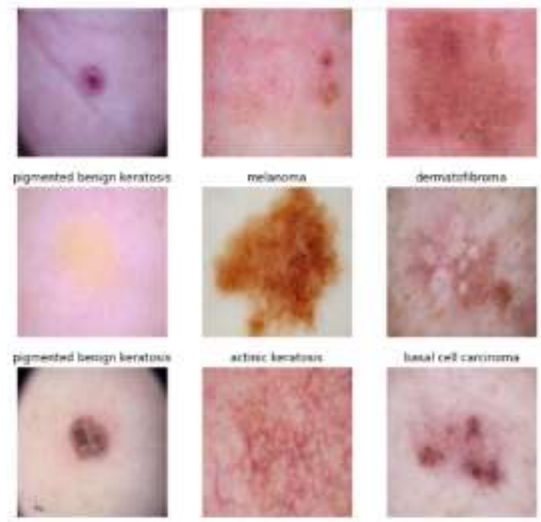

Fig 2 Dataset images

iv) Image Processing:

The flexible ImageDataGenerator is utilized in the image processing pipeline to augment and enhance pictures, which contributes to a more robust model. Afterwards, photos undergo re-scaling to ensure that the pixel values are identical throughout the entire dataset. This simplifies the extraction of features. Shear transformation is added to add controlled deformations that aids the model to identify the changes in the forms of skin lesions. The zoom enhances the dataset to appear as having varied angles and dimensions.

Horizontal flip is added to the training set by creating mirror images, thus enhancing the diversity of the dataset. Photo reconstruction ensures that they are compatible with the model architecture with varying input sizes. Another method of separating lesions is morphological Black-Hat transformation that highlights small structures in lesions. In the case of inpainting tasks, a mask is constructed to assist the algorithm in filling in missing or damaged sections in images. Lastly, gaps or flaws are filled to perfection using inpainting methods to produce a more complete and effective dataset to skin cancer detection models. This multi-faceted image processing approach does not only make the model more generalizable, but also addresses issues that may arise in the real world, which makes the model more efficient at diagnosing.

v) Algorithms:

ResNet50 is a 50-layer convolutional neural network which is also famous in resolving the vanishing gradient problem. It introduces skip connections, which allow the information to flow directly between layers, which facilitates the gradient flow in training. This is a wonderful architecture in image classification, which is demonstrated by its improved performance in DL competitions and real-world applications.

DenseNet169 is a 169-layer convolutional network that contains all layers that are densely connected. It is the thick block that makes it unique. This block has every layer directly fed by all the levels preceding it, and this promotes reuse of features. This causes parameters to work and resolves issues with disappearing gradients, improving accuracy. DenseNet169 is the best at image recognition, and it is particularly useful in cases where not a lot of training data is available.

VGG16 is a popular design of the convolutional neural network that contains 16 weight layers. It is easy and effective. It is also easier to learn features as it has a simple architecture, including multiple 3x3 convolutional layers. VGG16 continues to be a solution to image classification tasks due to its simplicity in learning and training, despite being superseded by more complex architectures**.**

Xception also known as Extreme Inception is a modification of Inception architecture that employs depthwise separable convolution as opposed to conventional convolutional layers. This transformation renders it easier to compute and maintains the expressive ability. Compared to the usual designs, Xception is more effective and efficient in classifying images and extracting features. Its hierarchical features are easier to learn due to its construction, making it suitable to a large variety of computer vision tasks.

DenseNet201 DenseNet201 is a variant of DenseNet that has 201 layers. It has more model capacity on it and thus can detect more complex patterns in the data. It has closely connected blocks, similarly to past DenseNet designs, to promote feature reuse and simplify gradient flow. DenseNet201 is the best to use in image classification because it possesses numerous parameters and deep networks that makes it more precise, in cases of a large amount of training data. It is powerful enough to process a broad spectrum of intricate visual patterns because of its design.

YOLOv5 is a real-time object detection algorithm that provides a reasonable compromise between speed and precision. It is based on convolutional neural network (CNN), which is aimed at efficiency and simplicity to set up. It aims at locating objects very precisely and yet at real time. It finds extensive applications in medical imaging, self-driving car and security cameras. It is capable of processing complex

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visual information with minimal processing capacity and can thus be useful in activities that require rapid and precise object localization.

YOLOv6 is an improved version of YOLO that is more efficient and accurate. It integrates superior methods of extracting features and of design of lightweight networks. The aim is to ensure that it offers quicker detection and more accuracy particularly in a situation of limited resources. It is commonly used in intelligent surveillance, medical diagnostics and industrial control. Its minimalist design can be used to a wide application as it can detect objects very fast and with utmost accuracy as it is accurate and fast in what it detects.

YOLOv7 is an innovative object detector known to have the best speed-accuracy tradeoff. It brings architectural transformations which include long backbone networks and enhanced model scalability. The key objective is to enhance real-time detection without compromising the accuracy. It is applied to such things as the analysis of medical images, autonomous navigation, and monitoring traffic. The optimized structure allows it to find objects accurately and it is applicable in complex environments where high detection rates with minimal delays are required.

YOLOv8 is the latest in the line of YOLO. It is based on the latest DL architecture to detect objects more effectively. It has a more suitable backbone and novel methods of feature combinations to achieve the best accuracy. The aim is to achieve very precise real-time detection that performs well on various datasets. It finds common application in medical diagnostics, smart city infrastructure and security surveillance. Its effective architecture enables it to locate complicated patterns and objects more precisely and faster than ever before.

4. EXPERIMENTAL RESULTS

Accuracy: The test accuracy is defined as the ability of a test to distinguish between weak and strong examples. To quantify the extent of accuracy of a test we ought to retain the few actual positives, and actual negatives of cases that have been exhaustively examined. This can be mathematically defined as:

Accuracy = TP + TN TP + TN + FP + FN.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

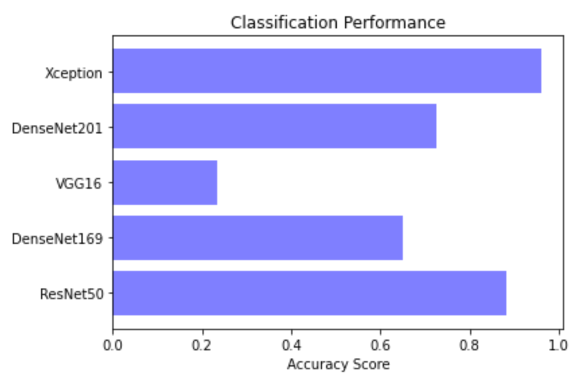

Fig 3 Accuracy Graph - Classification

Precision: Precision informs you of the number of the positives effectively identified. Due to this, to compute the accuracy you can make use of the following formula:

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Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

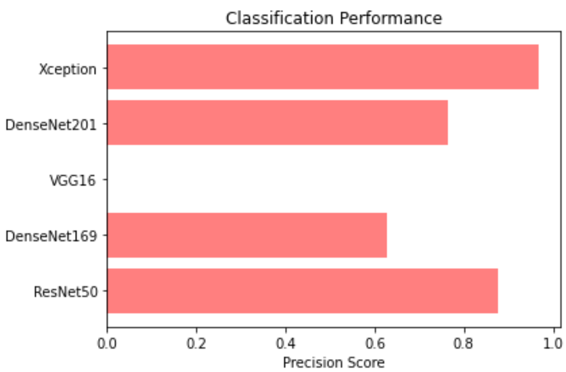

Fig 4 Precision graph - Classification

Recall: Recall in ML is a measure that investigates the ability of a model to locate all the pertinent samples of a specific category. It is the ratio of predicted favorable impressions correctly predicted to actual benefits that describes how well a model can locate examples of a particular class.

$$Recall = \frac{TP}{TP + FN}$$

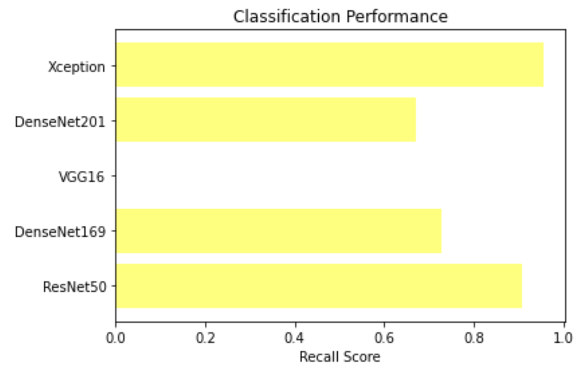

Fig 5 Recall graph - Classification

F1-Score: The F1 score is a measure used to determine the functionality of a ML model. It is a combination of accuracy and review scores of a model. The accuracy measure informs you of how many times a model has guessed correctly on the entire data.

$$\textbf{F1 Score} = \frac{2}{\left(\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}\right)}$$

$$\textbf{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

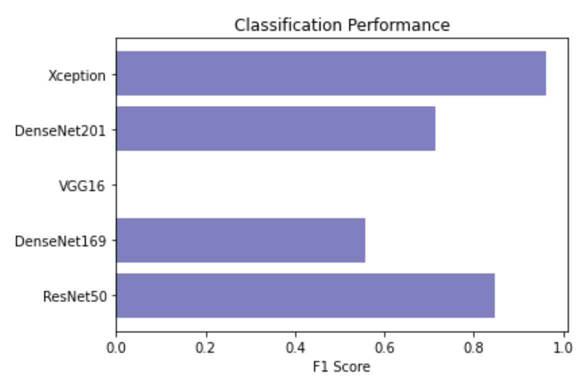

Fig 6 F1 Score graph - Classification

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Fig 7 Home page

Fig 8 Registration page

Fig 9 Login page

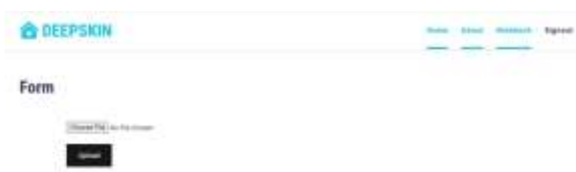

Fig 10 Upload input image page

Fig 11 input images folder

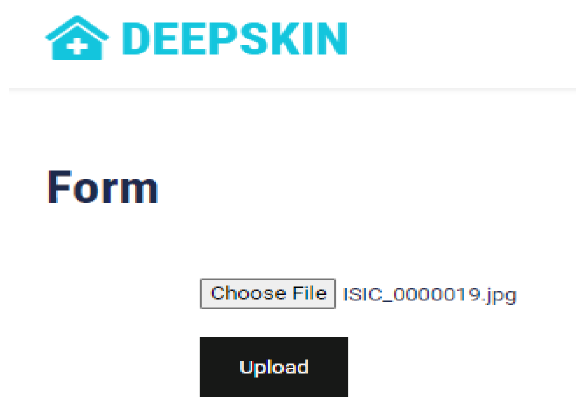

Fig 12 Upload input image to predict result

Fig 13 Final outcome as the patient is diagnosis with Nevus

5. CONCLUSION

In order to ensure that individuals seek treatment as early as possible and reduce the number of deaths, skin cancer identification and classification require precise and fast diagnostic instruments. Auto analysis of medical images has been enhanced significantly by DL, which provides us with more accurate methods of locating the lesions. The methods of detection and classification employed in this study are the most up-to-date and they are very successful in distinguishing between the various types of skin lesions.

YOLOv8 model was most successful in detecting lesions since it could easily and precisely detect objects. Xception was also the most accurate at the categorization since it was able to extract intricate features and distinguish between lesion types. The integration of these models enhances precision of diagnosis, which aids dermatologists to make superior decisions.

The powerful DL structures enable automatic detection of skin cancer more easily and quickly, which reduces false diagnoses and unnecessary biopsies. The high-performance models utilized in this research assist in improving patient care by facilitating easier detection of skin cancer at an early stage and precisely, which translates to improved treatment outcomes.

6. FUTURE SCOPE

The future of this research is further refining of the parameters, experimenting with ensemble models and applying novel DL architectures. Applying real-life information and continuously changing with new technologies will also take the system more precise and applicable in more clinical situations..

REFERENCES

[1] Y. C. Lee, S.-H. Jung, and H.-H. Won, ‘‘WonDerM: Skin lesion classification with fine-tuned neural networks,’’ 2018, arXiv:1808.03426.

[2] U. Jamil, M. U. Akram, S. Khalid, S. Abbas, and K. Saleem, ‘‘Computer based melanocytic and nevus image enhancement and segmentation,’’ BioMed Res. Int., vol. 2016, pp. 1–13, Jan. 2016.

[3] A. Mahbod, G. Schaefer, C. Wang, R. Ecker, and I. Ellinge, ‘‘Skin lesion classification using hybrid deep neural networks,’’ in Proc. IEEE Int. Conf. Acoust., Speech Signal Process. (ICASSP), May 2019, pp. 1229–1233.

[4] K. Pai and A. Giridharan, ‘‘Convolutional neural networks for classifying skin lesions,’’ in Proc. TENCON IEEE Region 10 Conf. (TENCON), Oct. 2019, pp. 1794–1796.

[5] A. S. Shete, A. S. Rane, P. S. Gaikwad, and M. H. Patil, ‘‘Detection of skin cancer using CNN algorithm,’’ Int. J., vol. 6, no. 5, pp. 1–4, 2021.

[6] M. Vidya and M. V. Karki, ‘‘Skin cancer detection using machine learning techniques,’’ in Proc. IEEE Int. Conf. Electron., Comput. Commun. Technol. (CONECCT), Jul. 2020, pp. 1–5.

[7] H. Nahata and S. P. Singh, ‘‘Deep learning solutions for skin cancer detection and diagnosis,’’ in Machine Learning with Health Care Perspective. Cham, Switzerland: Springer, 2020, pp. 159–182.

[8] P. Wighton, T. K. Lee, H. Lui, D. I. McLean, and M. S. Atkins, ‘‘Generalizing common tasks in automated skin lesion diagnosis,’’ IEEE Trans. Inf. Technol. Biomed., vol. 15, no. 4, pp. 622–629, Jul. 2011.

[9] J. Saeed and S. Zeebaree, ‘‘Skin lesion classification based on deep convolutional neural networks architectures,’’ J. Appl. Sci. Technol. Trends, vol. 2, no. 1, pp. 41–51, Mar. 2021.

[10] Y. Li, A. Esteva, B. Kuprel, R. Novoa, J. Ko, and S. Thrun, ‘‘Skin cancer detection and tracking using data synthesis and deep learning,’’ 2016, arXiv:1612.01074.

[11] V. Badrinarayanan, A. Kendall, and R. Cipolla, ‘‘SegNet: A deep convolutional encoder–decoder architecture for image segmentation,’’ IEEE Trans. Pattern Anal. Mach. Intell., vol. 39, no. 12, pp. 2481–2495, Dec. 2017.

[12] P. Tschandl, C. Rosendahl, and H. Kittler, ‘‘The HAM10000 dataset, a large collection of multi-source dermatoscopic images of common pigmented skin lesions,’’ Sci. Data, vol. 5, no. 1, pp. 1–9, Aug. 2018.

[13] K. M. Hosny, M. A. Kassem, and M. M. Foaud, ‘‘Skin cancer classification using deep learning and transfer learning,’’ in Proc. 9th Cairo Int. Biomed. Eng. Conf. (CIBEC), Dec. 2018, pp. 90–93.

[14] A. Javaid, M. Sadiq, and F. Akram, ‘‘Skin cancer classification using image processing and machine learning,’’ in Proc. Int. Bhurban Conf. Appl. Sci. Technol. (IBCAST), Jan. 2021, pp. 439–444.

[15] R. Ashraf, I. Kiran, T. Mahmood, A. U. R. Butt, N. Razzaq, and Z. Farooq, ‘‘An efficient technique for skin cancer classification using deep learning,’’ in Proc. IEEE 23rd Int. Multitopic Conf. (INMIC), Nov. 2020, pp. 1–5.