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SKIN CANCER IMAGE CLASSIFICATION USING DEEP LEARNING

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Abstract: This research highlights the need of precise detection for effective prevention of fast spreading skin cancer, which is an important worldwide concern. Because of the challenges with early detection, dermatologists have turned to deep learning, and more specifically, Convolutional Neural Networks (CNNs). The study uses data preparation methods like as sampling, dull razor, and autoencoder-based segmentation on the MNIST: HAM10000 dataset, which has 10,015 samples and seven different kinds of skin lesions. Utilizing transfer learning with DenseNet169 and ResNet50 models, it is shown that DenseNet169 achieves high accuracy and F1-measure by undersampling, while ResNet50 achieves excellence in both measures through oversampling. This extension builds on the base paper's work by utilizing additional models such as Xception and DenseNet201. The goal is to achieve a 95% improvement in accuracy. The study highlights the potential of diverse models and parameter tuning to improve skin cancer classification, which could lead to better diagnostic precision and preventive strategies.
Keywords:- Skin cancer, segmentation, CNN, Resnet50, Densenet201, Xception, and Densenet169 are index terms.

INTRODUCTION

When normally functioning cells undergo uncontrolled mutations and proliferation, a tumor is formed. Possible tumor types include malignant and noncancerous ones.Tumors that are malignant have the ability to metastasize, or spread to other parts of the body [6]. Although benign tumors may develop, they typically do not metastasize. Uncontrolled proliferation of skin cells leads to skin cancer. It is the most common cancer in the world right now, and it may happen anywhere. More than 3.5 million cases are reported annually due to different types of melanomas [7], [8]. When added together, their cases surpass those of colon, bone, and lung malignancies. Actually, every 57 seconds, someone loses their battle with melanoma. The survival rate is much improved when malignancy is identified in dermoscopy pictures beforehand. Autonomous skin excrescence finding that is both accurate and efficient will surely aid pathologists in their pursuit of excellence. Each melanoma patient's performance will be enhanced with the use of the dermoscopy technology. Dermoscopy is a noninvasive skin imaging technology that relies on a magnified and illuminated image of the afflicted skin region to better detect spots, while simultaneously minimizing reflections from the face [9]. A valuable asset is the ability to identify skin cancer early. The similarities between skin lesions make it hard to distinguish between benign and malignant ones. Among the many potential sources of skin cancer, the sun's UV radiation and UV tanning beds rank high. Because skin and lesions are so similar, doctors have a hard time telling the difference between melanoma and non-melanoma lesions [1]. The fundamental issue with shared viewpoints is that they are very subjective and difficult to replicate. Cases may get early opinion reports supported by data from deep literacy operations, which allows them to visit dermatologists for treatment [4]. There is a scarcity of treatment options for skin cancer, thus early detection is key. A skin cancer preventive strategy must include reliable assessment and the ability to detect skin cancer with precision. A large number of people have started using deep literacy even for unsupervised literacy activities [5]. On the subject of object identification and bracket problems, Convolutional Neural Networks (CNN) have been the undisputed leaders. Therefore, CNNs do away with the need for humans to manually generate feature sets when trained end-to-end in a controlled setting. Convolutional Neural Networks (CNNs) have recently surpassed human experts in skin cancer lesion classification.

Create a system that can automatically identify skin cancer using dermoscopy pictures and deep learning methods, particularly Convolutional Neural Networks (CNNs). This would improve early diagnosis. We want to enhance the precision of detecting cancerous and noncancerous tumors so that we can intervene quickly and boost survival rates. The system's ultimate goal is to improve the efficacy of melanoma patient treatment by assisting pathologists with quick and accurate analysis.There has been a dramatic rise in the incidence of skin cancer, particularly melanoma, which is a major public health concern. The present obstacle to early identification and prompt treatment is the difficulty in differentiating benign from malignant tumors. Dermoscopy is a helpful technique, but it is highly dependent on human judgment, which makes it unpredictable and hard to replicate. Because of this, there is an urgent need for a deep learning-based automated system to enhance diagnosis accuracy, which would allow for rapid intervention and fill the key void in efficient skin cancer treatment and prevention.

LITERATURE SURVEY

[1] Using an optimized Convolutional Neural Network (CNN) trained using the enhanced whale optimization technique, this research presents a new method for early skin cancer diagnosis based on image processing. The results show that it performs better when compared across two datasets. By using an upgraded convolutional neural network (CNN) and the modified whale optimization algorithm, the suggested system outperforms competing systems in terms of detection accuracy. The algorithm's intricacy and resource-intensive optimization are two potential downsides that might need a lot of time and computing resources. Problems include possible algorithm complexity, a lack of varied and representative datasets, and the high computing resources needed for optimization, all of which are necessary to guarantee robust performance over a wide range of skin kinds and situations. Using an optimized convolutional neural network (CNN) with the modified whale optimization algorithm, the research offers a potential technique for early skin cancer diagnosis. It outperforms other approaches, but has issues with processing needs and dataset variety.

[2] The use of deep convolutional neural network designs to tackle problems like dermoscopy picture quality difficulties is highlighted in this paper's evaluation of state-of-the-art deep learning ideas for skin cancer detection and classification. An innovative method for classifying skin lesions is offered by the suggested system, which makes use of state-of-the-art deep learning neural networks, particularly convolutional architectures. It deals with issues including noise, artifacts, and shadows that restrict dermoscopic imaging. Deep convolutional neural networks are complicated and resource-intensive, which might be a problem. Also, you should think long and hard about model interpretability and overfitting. We need strong methods to manage different kinds of skin lesions and morphological characteristics, and we also need to consider the influence of dermoscopic picture quality difficulties on correct classification. Additionally, we need to consider the possible computing resource needs. In this study, we survey the state of the art in skin cancer detection using deep convolutional neural networks, focusing on how these networks can overcome obstacles in dermoscopy pictures. Although it shows promise, tackling computational challenges and making sure it is resilient are very important for making it work in the real world.

[3] An image processing and machine learning skin cancer classification system is presented in this paper. The following steps are taken: contrast stretching, segmentation using OTSU thresholding, feature extraction using GLCM, HOG, and color, PCA reduction, SMOTE sampling, and classification using Random Forest. The accuracy achieved on the ISIC-ISBI 2016 dataset was 93.89% after this. When it comes to skin cancer categorization, the method is very accurate (93.89%), which means it may help with early diagnosis. It provides a strong solution for dermatologists by effectively combining contrast stretching, feature selection, and Random Forest classification. Scalability and real-time processing might be obstacles to the system's high accuracy. Its performance may differ across different datasets and clinical contexts, and it demands a lot of computer resources. Problems in handling varied skin conditions outside the dataset utilized and its dependency on specialized algorithms restrict flexibility are potential issues with the proposed system. Furthermore, further testing and validation may

be necessary for real-world deployment. Skin cancer classification is improved by combining Random Forest classification, feature selection, and contrast stretching. The technology shows potential in helping dermatologists with early detection, however there are several practical hurdles and more validation needed before it can be used in the real world.

[4] The goal of this research is to employ machine learning and image processing to identify and categorize skin cancers. It uses color-based k-means clustering for segmentation after dermoscopy picture pre-processing, which includes hair removal and Gaussian filtering. A combination of ABCD criteria and GLCM is used for feature extraction. On the ISIC 2019 Challenge dataset, Multi-class Support Vector Machine (MSVM) attains an accuracy of 96.25 percent. When tested on a variety of skin cancers, the method obtains an impressive level of accuracy (96.25%). Its effectiveness in early detection and classification is enhanced by integrating robust feature extraction, color-based segmentation, and thorough pre-processing algorithms. Scalability and adaptation to varied datasets may be obstacles for the system, despite its excellent accuracy. Its use in many real-world contexts may be compromised due to its dependence on certain pre-processing procedures and classifiers. When applied to skin situations outside of the dataset under consideration, the suggested system may fail. Because it presupposes that dermoscopy pictures are homogenous, further validation and customization to various clinical contexts may be necessary for its practical use. This method achieves a remarkable level of accuracy (96.25%) in skin cancer detection and classification by using sophisticated pre-processing, segmentation, and MSVM classification. Further validation and modification to varied clinical circumstances are necessary for practical deployment, however its holistic approach does improve early detection skills.

[5] The goal of this project is to combine Python, Keras, and Tensorflow to build a Convolutional Neural Network (CNN) model that can identify skin cancer. The model uses deep learning to identify different forms of skin cancer and classify them using several network topologies, such as Convolutional, Dropout, Pooling, and Dense layers. This allows for early identification. The dataset is derived from the archives of the International Skin Imaging Collaboration (ISIC) challenge, and Transfer Learning is used to improve convergence. Convolutional Neural Networks (CNNs), which are renowned for their exceptional accuracy in visual imaging tasks, are used by the system. Thanks to Python's Keras and Tensorflow, it's both efficient and flexible. Faster convergence is possible with the help of Transfer Learning, and a solid assessment framework is provided by testing on the ISIC dataset. Although it works, the suggested approach could have trouble being understood since deep learning models are inherently complicated. Furthermore, training could be resource-intensive, and overfitting is a real possibility; hence, optimization and tweaking are essential. Because the ISIC dataset does not fully capture a wide variety of skin diseases, the system may struggle to generalize to these circumstances. Possible roadblocks to practical implementation include processing costs, difficulties with interpretability, and the requirement for huge labelled datasets. This study highlights the significance of early diagnosis by demonstrating the potential of convolutional neural networks (CNNs) in skin cancer detection. To improve the performance of the models, we apply Transfer Learning in conjunction with various network topologies. Although it shows promise, solving problems like interpretability and dataset representativeness is essential for putting it into practice.

METHODOLOGY

i) Our suggested method uses Convolutional Neural Networks (CNNs) to identify skin cancer in a way that is state-of-the-art, outperforming previous standards in object identification and classification. A dataset called MNIST: HAM10000, which contains 10,015 samples of seven different skin lesion types, was painstakingly selected for this study. In order to prepare the dataset for rigorous experiments, essential data pre-processing methods are used, including as sampling, dull razor, and autoencoder-based segmentation.

Using the DenseNet169 and ResNet50 models to train the CNN is fundamental to our approach, which focuses on using transfer learning methods. With the use of undersampling and oversampling strategies,

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we can compare different transfer learning models and see how they affect performance indicators. Our expansion adds sophisticated models such as Xception and DenseNet201, expanding upon the main paper's investigation of ResNet50, DenseNet161, and VGG16, which achieved 91% accuracy. Improving skin cancer diagnosis via the investigation of new classification approaches and model architectures is possible, as this diversification intends to push the classification accuracy to 95%.
ii) System Architecture: Convolutional Neural Networks (CNNs) are included into the proposed architecture of the skin cancer detection system to ensure accurate object recognition and categorization. A dataset obtained from MNIST: HAM10000 is used for pre-processing, which includes methods like sampling, dull razor, and autoencoder-based segmentation. The dataset contains 10,015 samples of seven different kinds of skin lesions. At its heart, the system makes use of transfer learning using models trained on the pre-processed data, namely DenseNet169 and ResNet50. These models' undersampling and oversampling capabilities are compared in a comparative study. With its flexible and scalable design, the system architecture has the power to revolutionize dermatological diagnostics by using state-of-the-art neural network topologies and model selection.

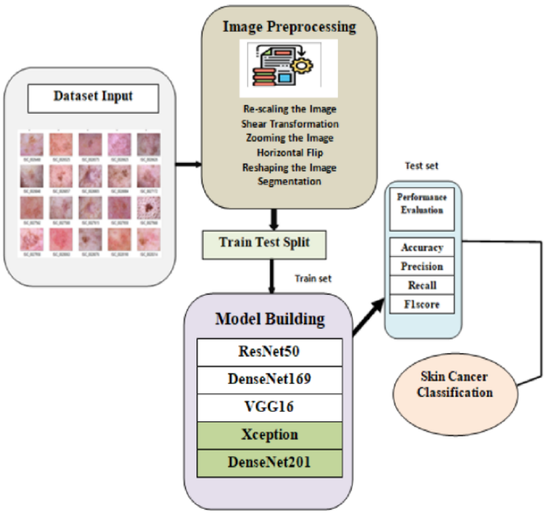

Fig 1 System Architecture
iii) Dataset Collection: For the sake of a notebooks project, we have reuploaded a subset of the HAM10000 dataset called the Skin Cancer Data dataset. In order to make this curated dataset more useful and relevant, it has been processed with great care. A wide variety of skin lesion types are used to compile the extensive data pertaining to skin cancer. The dataset offers a diverse and extensive collection for research and experimentation, with a total of 10,015 samples. Data quality is optimized throughout processing by using strategies like sampling and using methods like autoencoder-based segmentation and dull razor. These procedures ensure that a representative sample of data is used. With its refined and processed collection, this curated dataset provides dermatological researchers and practitioners with a significant resource for dermatological investigations. It helps them get important insights and advances skin cancer diagnosis and categorization.

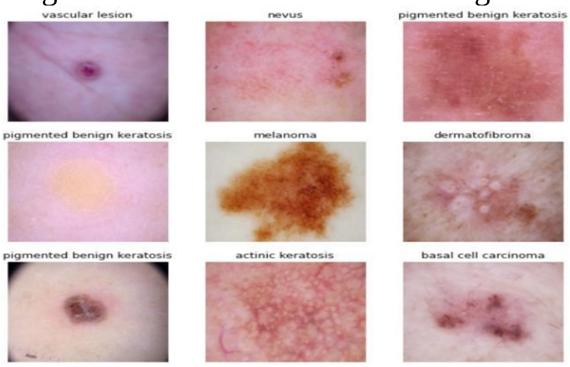

Fig 2 Dataset images

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1. Nevus:- Skin mole or birthmark lesion.
2. Melanoma:- Develops from melanocytes and can spread rapidly if not treated early.
3. Basal cell carcinoma:- Slow-growing skin cancer that develops in the basal cells of the epidermis.
4. Vascular lesion:- Abnormal growth in blood vessels, potentially requiring treatment.
5. Dermatofibroma:- Benign skin growth, often firm, brownish, harmless lesion.
6. Actinic keratosis:- Pre-cancerous rough skin lesion.
7. Pigmented benign keratosis:- Noncancerous, dark skin growths.

iv) Image Processing: The image processing pipeline uses the flexible ImageDataGenerator to increase the model's resilience by supplementing and improving pictures. Image rescaling is the first step in achieving uniform feature extraction across all datasets by standardizing pixel values. To help the model identify different forms of skin lesions, shear transformation adds controlled deformations. By creating the illusion of several magnifications and viewpoints, zooming improves the dataset.

By creating mirror images, horizontal flip diversifies the dataset and increases the size of the training set. Image resizing allows for a variety of input dimensions, which is necessary for model architectural compatibility. In order to further separate lesions, segmentation methods are used, with morphological black-hat transformation serving to emphasize fine features. For inpainting jobs, a mask is made to direct the algorithm in reassembling damaged or missing areas of pictures. Last but not least, inpainting techniques are used to fill in defects and gaps, creating a more complete dataset for skin cancer detection models. Ultimately, the model's diagnostic skills are improved by this multi-faceted image processing technique, which also increases model generalization and solves possible problems in real-world settings.

section

v) Processes: Famous for solving the vanishing gradient issue,

ResNet50:

It is a 50-layer convolutional neural network design. By introducing skip connections, it improves gradient flow during training by letting information flow straight across layers. This architecture has shown to be very effective in picture classification problems, both in real-world applications and deep learning contests.

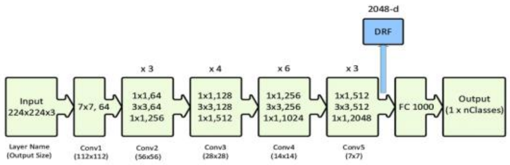

Fig 3 ResNet50 architecture

DenseNet169:

With 169 layers, DenseNet169 is a highly linked convolutional network. The dense block is its defining characteristic; in this architecture, feature reuse is encouraged by having all levels directly input from all layers below it. This improves accuracy by increasing parameter efficiency and reducing vanishing gradient problems. When faced with situations when there is a lack of training data, DenseNet169 really shines in picture recognition tasks.

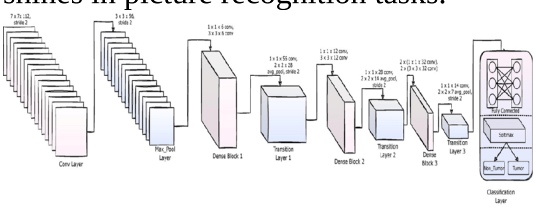
Fig 4 DenseNet169 architecture

VGG16:

One well-known and efficient convolutional neural network design is VGG16, which has 16 weight layers. Its feature learning is facilitated by its basic architecture, which comprises several 3x3 convolutional layers. Despite being overtaken by deeper architectures, VGG16 is still considered a gold standard for image classification problems because of how easy it is to learn and train.

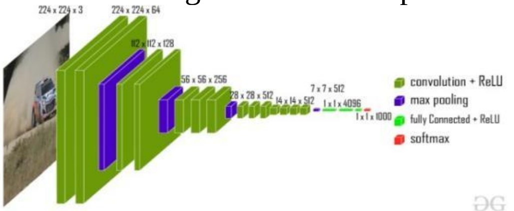

Fig 5 VGG16 architecture

Xception:

"Xception" stands for "Extreme Inception," and it's an enhancement to the Inception architecture that uses depthwise separable convolutions instead of the usual convolutional layers. This change lessens the computational burden without sacrificing expressive capability. Xception outperforms conventional designs in picture categorization and feature extraction, revealing significant efficiency gains. Its architecture is ideal for a wide range of computer vision tasks because it facilitates the learning of hierarchical features.

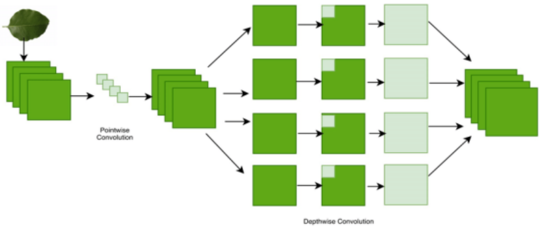

Fig 6 Xception architecture

DenseNet201:

An enhanced model capability for collecting complicated patterns in data is provided by DenseNet201, a variation of DenseNet with 201 layers. Like previous DenseNet designs, it makes use of densely linked blocks to promote feature reuse and ease gradient flow. With its many parameters and deep architectures, DenseNet201 achieves better accuracy in picture classification tasks, which is especially helpful when there is a lot of training data. It can handle complex visual patterns with ease because of its design.

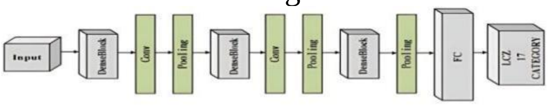

Fig 7 DenseNet201 architecture

EXPERIMENTAL RESULTS

Accuracy: The capacity of a test to accurately identify weak and strong instances is called its accuracy. We should record the insignificant portion of true positive and true negative results in fully studied instances to measure the accuracy of a test. One way to express this quantitatively is as:

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

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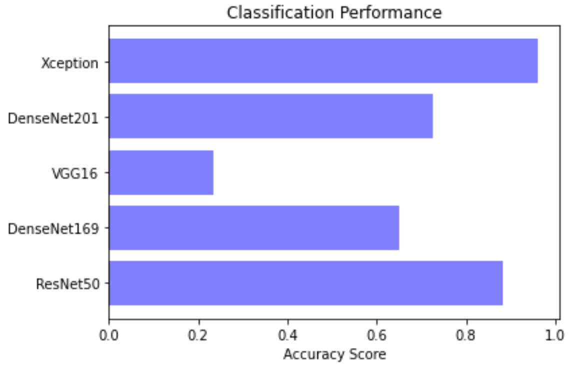

Fig 8 Accuracy Graph

Precision: The fraction of correctly classified events or samples among the positives is what precision measures. This leads to the following formula for determining the accuracy:

Preciseness is TP divided by (TP plus FP), which is the sum of true positives and false positives.

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

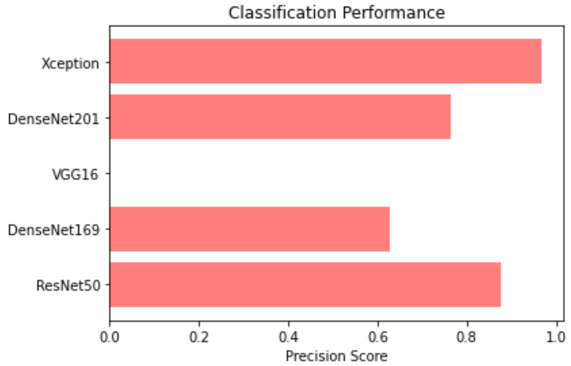

Fig 9 Precision graph

Recall: The ability of a model to identify all relevant instances of a given class is evaluated using the machine learning measure recall. You can tell a model is good at catching occurrences of a certain class by looking at the percentage of correctly predicted positive impressions to total positives.

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

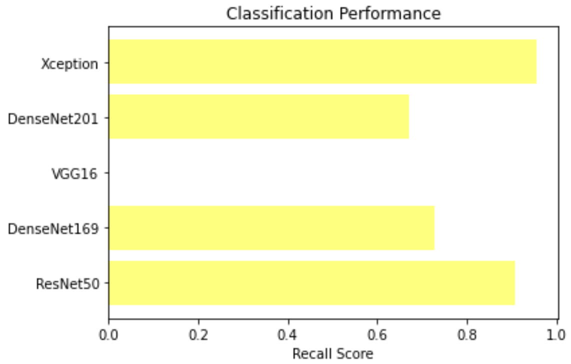

Fig 10 Recall graph

F1-Score: One way to test a model's accuracy in machine learning is via the F1 score. The accuracy and evaluation ratings of a model are combined. To find out how frequently a model got the whole dataset right, we may use the precision metric.

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

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

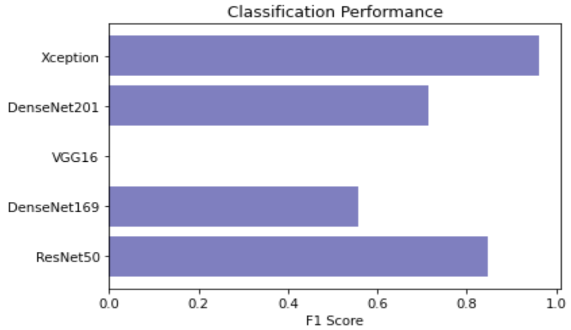

Fig 11 F1 Score graph

Fig 12 input images folder

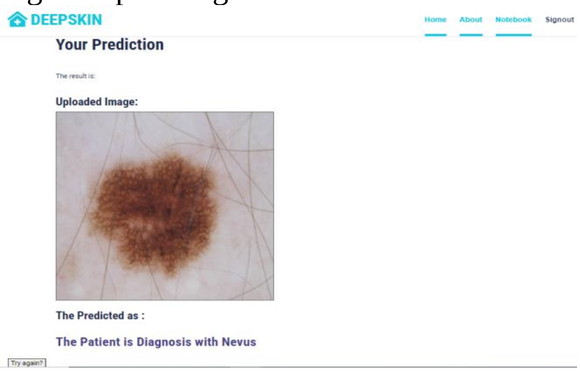

Fig 13 Final outcome as the patient is diagnosis with Nevus

	ML Model	Accuracy	Precision	Recall	F1_score
0	ResNet50	0.884	0.876	0.909	0.847
1	DenseNet169	0.649	0.629	0.728	0.558
2	VGG16	0.233	0.000	0.000	0.000
3	DenseNet201	0.725	0.765	0.672	0.714
4	Xception	0.962	0.969	0.957	0.963

Fig 14 Performance Evaluation Table

The table compares ML models' performance on wheat stripe rust disease classification. Xception leads in accuracy (0.962) and precision (0.969), indicating accurate and reliable predictions. ResNet50 excels in recall (0.909), capturing most diseased cases. Xception also boasts the highest F1 score (0.963), indicating superior overall performance for this task.

CONCLUSION

We conclude that Convolutional Neural Networks (CNNs) combined with a HAM10000 dataset that has been painstakingly analyzed show promise in the identification of skin cancer. Our models demonstrate strong performance in object identification and classification by using transfer learning with DenseNet169 and ResNet50. A foundation for strategic selection in skin cancer diagnostic applications is provided by the comparative study of undersampling and oversampling strategies, which provide deep insights about model behavior.

In addition, our expansion investigates new models including Xception and DenseNet201 with the goal of achieving a 95% or above improvement in accuracy in which Xception leads in accuracy with 96%. Model generalizability and dataset variety are both improved by using state-of-the-art image processing methods including shear transformations, zooming, and morphological modifications. The inpainting approach fixes any flaws and adds to the completeness of the dataset. Along with adding to the ever-changing field of dermatological diagnostics, our study highlights the significance of ongoing research and improvement. We expect a big improvement in skin cancer detection accuracy by using various image processing techniques and state-of-the-art models, which will lead to better dermatological preventative and diagnostic measures.

FUTURE SCOPE

Future research could explore combining advanced image processing methods with ensemble models and incorporating multimodal data to enhance skin cancer detection accuracy and facilitate more effective dermatological preventative and diagnostic measures.

PROJECT OUTLINE

Additional work on optimizing parameters, investigating ensemble models, and incorporating new deep learning architectures are all in the works for the future of this project. The accuracy and usability of the system in various clinical contexts will be further improved by including real-world datasets and continuously adapting to emerging technology.

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