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Skin Cancer Classification using YOLO-NAS based Convolutional Network with Modified Focal Loss

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ABSTRACT
This work presents a novel approach for skin lesion classification through the utilization of a YOLO-NAS (You Only Look Once Neural Architecture Search) based convolutional network. Leveraging the speed and efficiency of YOLO's object detection algorithm and the automated architecture design capabilities of NAS, the system achieves advanced levels of classification accuracy while maintaining real-time processing capabilities. By seamlessly integrating object detection and neural architecture search, the proposed YOLO-NAS based convolutional network with modified focal loss offers a promising solution for efficient and effective skin lesion classification, thereby contributing to improved early diagnosis and timely medical interventions for dermatological conditions. On the ISIC-2019 dataset, this technique obtains an accuracy of 92.00%, an average precision of 92.12%, an average recall of 92.37%, and an average F1-score of 92.12%.

KEYWORDS
Deep Learning, Skin lesion classification, HAM10000 dataset, Skin lesion classification

1. INTRODUCTION

The automation of identifying and categorizing skin lesions a crucial task in contemporary dermatology, especially when diagnosing skin cancer. Manually evaluating skin lesions by dermatologists can be both time-consuming and subjective, resulting in inconsistencies in diagnoses and the possibility off delayed treatment. To tackle these difficulties, scientists have investigated different computational methods to create automated systems that detect and categorize skin abnormalities precisely.

Automated classification systems face a daunting challenge due to the intricate nature of skin lesions and the wide range of possible variations in their appearance. Lesions can display various attributes including colour, shape, texture, and size. complicating their precise categorization. Furthermore, differentiating between harmless and cancerous abnormalities introduces an extra level of intricacy since misidentifying them can result in critical medical consequences.

Although there are difficulties, the potential advantages of automated skin lesion classification systems are enormous. By utilizing sophisticated machine learning and computer vision methods, these systems can swiftly and consistently evaluate skin abnormalities, assisting dermatologists in promptly and precisely diagnosing conditions. Moreover, these systems have the potential to enhance the availability of dermatological care in areas that need more specialized knowledge.

There has been a recent increase in interest in creating strong and dependable automated systems for classifying skin lesions [1]. The progress in deep learning has been driven by advancements in convolutional neural networks (CNNs), specifically in image recognition tasks. Researchers have obtained promising outcomes in accurately classifying skin lesions as benign or malignant and identifying specific forms of skin cancer by training Convolutional Neural Networks (CNNs) on extensive datasets of annotated skin lesion images [2]– [5].

Nevertheless, despite these progressions, numerous obstacles persist. Fluctuations in imaging conditions, such as illumination and camera perspective, can introduce irregularities that impact the efficiency of automated classification systems. Furthermore, ensuring these systems can be applied to a wide range of populations and skin types is crucial to maximize their usefulness in clinical settings.

Automated skin lesion classification systems are an exciting area of advancement in dermatology. Through machine learning and computer vision, these systems can completely transform the process of diagnosing and treating skin cancer. Ultimately, enhancing patient results and preserving lives. Numerous methods have been employed by researchers, including deep learning models, neural networks, and the K-Nearest neighbor (KNN) algorithm [6]– [14]. To increase classification accuracy, some research has concentrated on combining characteristics such the fractal dimension of the skin surface and color distribution [15].

Others have investigated combining machine learning classifiers with pre-trained convolutional neural networks (CNN) as feature extract Orto achieve high accuracy in skin lesion classification [16],[17].

Additionally, attention- and residual-learning-enhanced densely connected convolutional networks have been developed, and they exhibit improved classification accuracy for skin lesions [18]. These methods seek to offer precise and effective ways to categorize skin lesions, assisting dermatologists in their diagnosis.

Bhardwaj and Rege [19] proposed a deep learning technique for the classification of skin diseases. It used a support vector machine (SVM) and a combination of top-performing mode lass feature extractors. This model achieved 86% accuracy on the ISIC 2019 dataset and had precision and recall values of 0.8 and 0.6 respectively.

DeVries and Rama Chandran [17] presents a deep learning approach for skin cancer classification using a multi-scale convolutional neural network (CNN). The method uses anInception-v3 network fine-tuned for skin cancer classification using two different scales of input images. The proposed approach got overall accuracy of 0.874 on the ISIC-2017, outperforming the baseline method. The model incorporates controlled layer unfreezing for fine-tuning, deals with gradient problems, and uses mini-batches and oversampling to reduce training set overfitting.

Ratul et al. [20] proposed a method using InceptionV3and Mobile-Net networks to classify skin lesions. This

Method using fine-tuning and dilation rates improved overall accuracy on a challenging dataset with class imbalances. Jing et al. [21] proposed a method for classifying skin lesions that makes use of a highly linked neural network with residual learning and attention. The proposed model uses attention mechanisms and residual learning in dense and transition blocks without adding more parameters. This keeps classification accuracy while cutting network parameters in half. The model received high accuracy and area under the curve scores in the classification of skin lesions when tested on the ISIC 2016 and ISIC 2017datasets.

Samanta and Rout [22] use transfer learning on a trained VGG-Net to introduce an automatic skin lesion classification system. The proposed method helped dermatologists and healthcare workers achieve high accuracy (98.02%), sensitivity (98.10%), and specificity (97.05%) in differentiating malignant and benign skin lesions.

Abhishek et al. [23] introduce a system for classifying skin lesions that use different deep learning architectures. The method achieves over 80% accuracy in classifying various skin lesion types by combining pre-trained CNNs like Mobile-Net and VGG-16 with custom models. The authors

propose embedding their models in skin lesion analyzers for informed pre-diagnosis and reducing unnecessary alarms to address the issue of limited data by enhancing the HAM10000 dataset.

Literature Review is shown in . Xiaoxia et al. [24] proposed a method for analyzing skin lesions for melanoma detection, which combines deep CNNs with low-level image feature descriptors that closely resemble clinical criteria. The technique consists of two stages: modifying CNNs for feature extraction and using Light GBM to fuse and select key feature On the ISIC 2018 dataset, the method shows promising accuracy.

Renny et al. [25] introduce an ensemble learning approach that combines three deep CNN architectures for skin lesion classification achieving 97.23% accuracy, 90.12% sensitivity, and 97.73% specificity. The contributions include suggesting the ensemble approach, showing promise in skin lesion classification for cancer diagnosis, and achieving strong classification performance on a diverse dataset of dermo copy images.

On the ISIC-17 dataset, Iqbal et al. [27] proposed a Deep-Convolutional neural network model with many layers and minimal filters and parameters, and they were able to achieve 0.964 AUCROC.

Contributions:

- Developed a framework for skin lesion classification using YOLO-NAS based Convolutional network.
- Customized focal loss function for ISIC-2019 dataset which emphasizes more on difficult samples.

2. EXPERIMENTS AND METHODS

2.1 Data Preparation

The dataset used for evaluation in this work is ISIC-2019. The description of the dataset is shown in

Table 2. It has eight classes as apiece, bcc, bkl, df, nv, vasc, mel, scc.

The dataset shows a significant imbalance in the number of samples in each class. While some classes like ``nv" and ``me l"have a sizable number of samples, others like "scc," ``vasc,"and "df" have noticeably fewer samples. Class imbalance can affect the performance of machine learning models because the dominance of majority classes may make it difficult for minority classes to learn effectively. This imbalance is addressed using data augmentation. Data Image Generator with rotation range of 20 and height and width shift range of 0.2. Each image underwent cropping during the pre-processing stage to become a square image with the lesion's centre visible in the centre of each corresponding image

2.2 Evaluation Metrics

For evaluation of the effectiveness of the proposed model, the following evaluation metrics are used:

• **Accuracy**: The proportion of correctly predicted instances to all the dataset's instances. Although it is a general indicator of model performance, it may not be appropriate for datasets with imbalances.

• **Precision**: The proportion of accurate positive predictions to all the model's positive predictions. It gauges the model's proficiency at avoiding erroneous positive predictions.

• The ratio of true positive predictions to all the actual positive instances in the dataset is called **recall**. It gauges

how accurately the model captures instances of success.
• **F1-Score** is the harmonic mean of recall and precision. It offers a balanced measurement of precision and recall and is particularly helpful when there is a class imbalance.
• **Area under the receiver operating characteristic curve or AUC-ROC** is the degree to which the model may differentiate between positive and negative classes at various thresholds shown under the ROC Curve.
• **Area Under the Precision-Recall Curve (AUC-PR)** is comparable to Area Under the ROC Curve (AUC-ROC) but focuses on precision and recall. When working with unbalanced datasets, it is beneficial.

Table 1 Literature review summary for skin cancer

Reference and Year	Model proposed	Performance
Bhardwaj and Rege [19] (2021).	The authors suggest a method combining theist feature extraction models with a Support Vector Machine (SVM) to classify diseases	On the ISIC 2019 dataset, the neural network achieved 86% accuracy, with high precision and recall values of 0.8 and 0.6, respectively
Ratul et al. [20] (2019).	Dilated InceptionV3 performed well on the classification of skin lesions while dealing with a challenging open-source dataset with class imbalances.	Skin cancer is considered one of the deadliest types of cancer. The proposed model outperforms known methods in skin lesion classification.
Jing et al. [21] (2020).	This work contributes to the classification of skin lesions by addressing the problems of intra-class variation and inter-class similarity brought on by various imaging techniques and clinicopathology.	It achieves accuracy of 85.7% and AUC of 83.7% ion ISIC 2016 dataset and an average AUC of 91.8%on ISIC 2017.
Samanta and Rout [22] (2021).	The method utilizes transfer learning with VGG-Net, fine-tuning, data augmentation, and cross-validation to achieve remarkable classification accuracy.	Proposed method achieved a classification accuracy rate of 98.02% - Sensitivity of 98.10% and Specificity of 97.05%
Abhishek et al. [23] (2020).	The work focuses on categorising various skin lesions with an accuracy of above 80% utilising deep learning architectures like Mobile-net, VGG-16, and a custom model, including basal cell carcinoma, benign keratosis, dermatofibroma, vascular lesions, melanoma, and melanocytic nevi.	Skin lesions can be classified with high accuracy of80%. Deep learning architectures can aid in early detection.
Xiaoxia et al. [24] (2018).	The technique combines clinical criterion representations and deep-learning features for classifying skin lesions. It uses Light-GBM for feature fusion for diagnosis confidence prediction and customized CNNs to extract global features.	Proposed method achieved promising accuracies on skin lesion classification. - Fusion model using Light-GBM demonstrated effectiveness in classification.
Renny et al. [25] (2021).	Deep convolutional neural network (DCNN) architectures are merged in an ensemble learning technique to categorize skin lesions.	Ensemble learning approach improves skin lesion classification Proposed model achieves high accuracy and performance
Qasim et al. [26] (2023)	This study used deep spiking neural networks to categorise 3670melanoma and 3323 non-melanoma photos from the ISIC 2019 dataset using the surrogate gradient descent approach.	It achieved classification accuracy of 89.57% and anF1 score of 90.07%

2.3 Methods

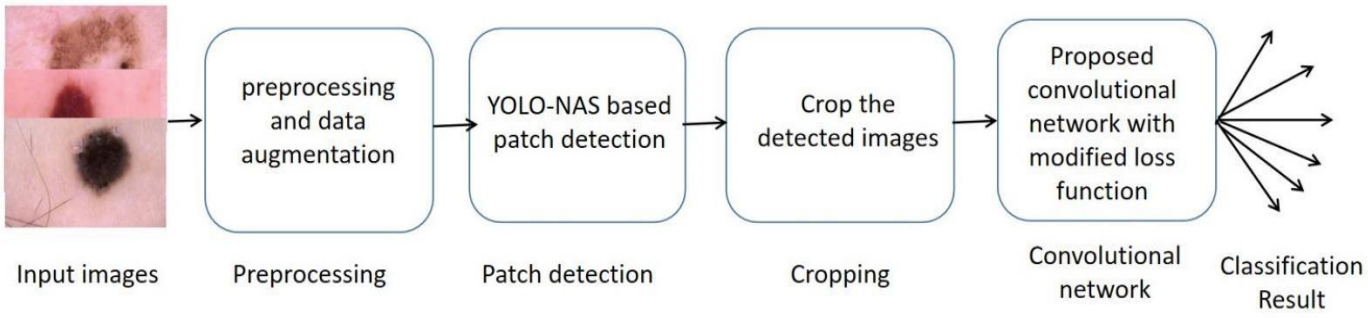

Fig. 1 Complete Framework model

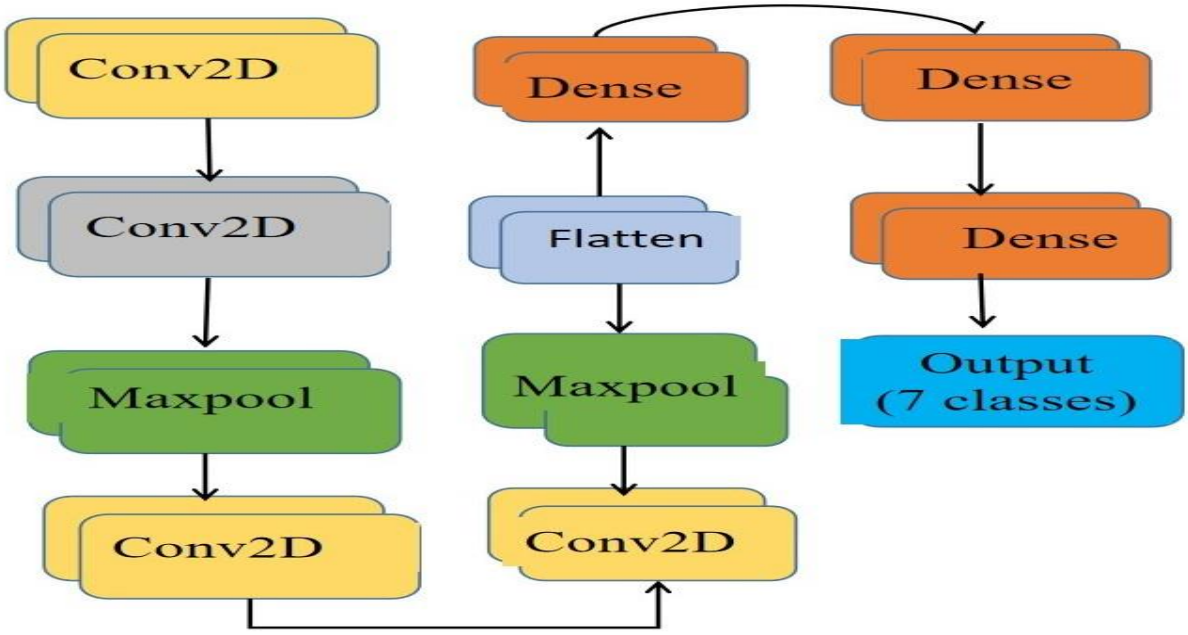

Fig. 2 Framework Model of the proposed Figure 3 .

This work uses You Only Look Once Neural Architecture Search (YOLO-NAS) [28] based convolutional network customized for locating skin lesion patch. YOLO-NAS, is an acronym for the phrases" You Only Look Once" and" Neural Architecture Search."

The object detection algorithm YOLO (You Only Look Once) is renowned for its quickness and effectiveness. YOLO performs object detection in a single pass through the network instead of conventional object detection techniques, which require several steps. It indicates that it derives directly from the input image predictions of the object's class and bounding box location. YOLO can assist in locating and identifying potentially cancerous areas in the image when used to classify skin lesions patch.

Automating the design of neural network architectures is known as NAS (Neural Architecture Search). It entails looking for the best architecture to complete a particular task. This method can significantly reduce the need for manual design and trial-and-error, leading to more effective and efficient models.

Classification and Localization of patch: The network simultaneously predicts the skin patch and its location within the image. Compared to conventional approaches, the YOLO architecture's single-pass prediction makes the process faster and more effective. It helps in the immediate diagnosis and evaluation of skin lesions.

Table 2 ISIC-2019 dataset description

Classes	Class code	Number of samples
apiece	3	867
bcc	2	3222
bkl	4	2624
Df	5	239
Nv	1	12874
vasc	6	253
mel	0	4521
scc	7	628

convolutional network

Modified Focal loss-: The Focal Loss [29] is a modified that emphasises difficult-to-classify samples during training in order to address class imbalance. Its mathematical formulation is as follows:
Let: - y_{true} be the true one-hot encoded class labels of shape (batch size, num classes). - y_{pred} be the predicted logits (raw output scores) of shape (batch size, num_classes). - ptrue be the true class probabilities obtained by applying softmax to ypred . - α be the focal factor that controls the balance between easy and hard samples. - γ be the focusing parameter that adjusts the focus on hard-to-classify samples. The Focal Loss is defined as

$$Focal\ Loss\ (y_{true}, y_{pred}) = -\alpha \cdot (1 - p_{true})^{\gamma} \cdot y_{true} \cdot \log (p_{true})$$

$$Focal\ Loss\ (y_{true}, y_{pred}) = -0.6 \cdot (1 - p_{true})^{2.1} \cdot y_{true} \cdot \log (p_{true})$$

Here's a step-by-step breakdown of the formula:

1. Compute the standard cross-entropy loss between the true class labels and predicted logits:

$$Cross\ Entropy = -y_{true} \cdot \log (p_{true})$$

2. Apply the soft-max function to the predicted logits to obtain class probabilities:

$$p_{true} = \text{softmax}\,(y_{pred})$$

3. Compute the focal weights that emphasize hard-to-classify samples:

$$Focal\ Weights = (1 - p_{true})^{\gamma}$$

4. Adjust the focal weights using the balancing factor α:

$$Adjusted\ Weights = \alpha \cdot Focal\ Weights$$

5. Multiply the adjusted focal weights with the cross-entropy loss to obtain the final Focal Loss:

The complete framework of the proposed model is shown in Fig. 1. The framework of the proposed convolutional network is shown in

Fig. 2. First the input images are preprocessed and data augmentation applied, which is then passed to YOLONAS module for patch detection. The detected patch is then cropped from the images. cropped from the images.

1 Complete Framework model

$$\text{Focal Loss} = \text{AdjustedWeights} \cdot \text{CrossEntropy}$$

The Focal Loss gives more weight to misclassified or uncertain samples (small p true) while down-weighting easy-to classify samples (large p true). The α parameter determines the strength of the down weighting, and the γ parameter controls the degree of focus on hard samples. From cross-validation and hold-out validation experiments on this ISIC-2019 dataset, the optimal value α = 0.6 and γ = 2.1 chosen. So, this modified focal loss is used in the proposed model for the ISIC-2019dataset help in achieving remarkable performance. Results are discussed in the next section.

3. RESULT

The classification report of the proposed model on ISIC 2019 dataset is shown in Table 3. It is clear from class-by class analysis of the results that the YOLO NAS-based model excels at differentiating between various types of skin cancers. Higher recall values for classes such as 5, 6, and 7 show that the model successfully correctly classifies those cancer types. Similarly, classes 3, 5, 6, and 7 with high precision value simply that the model produces reliable predictions for these classes.

Table 3 Classification Report of YOLO-NAS based

Class names	Precision	Recall	F1-score
akiec(3)	0.97	0.99	0.98
bcc(2)	0.92	0.94	0.93
bkl(4)	0.84	0.93	0.88
df(5)	0.99	1.00	1.00
nv(1)	0.83	0.69	0.75
vasc(6)	0.99	1.00	0.99
mel(0)	0.85	0.84	0.85
scc(7)	0.98	1.00	0.99
Average precision		92.12%	
Average Recall		92.37%	
Average F1-score		92.0%	
Accuracy		92%	

The model's performance is balanced across all classes, according to the 0.92 macro average F1-score and 0.92 weighted average F1-score. This suggests that the convolutional network built on the YOLO NAS platform can accurately classify a range of skin cancer types.
Another crucial metric for gauging the effectiveness of the classification model is the receiver operating characteristic (ROC) curve area. Values near 1.00 on the ROC curve area signify excellent model performance. The precision-recall graph of the proposed model on ISIC 2019 dataset is shown in Fig. 4 Proposed method Precision-recall graph on ISIC-2019dataset. The model's robustness in classifying different types of skin cancer is highlighted by the ROC curve areas of 0.98,0.96, 0.99, 1.00, 0.99, 1.00, and 1.00 for classes 0 through 7, respectively.

The high overall accuracy of 0.92 and the high ROC curve areas and F1-scores across different classes indicate that the YOLO NAS-based convolutional network is an effective tool for classifying skin cancer. The outcomes give confidence that this strategy has the potential to help doctors accurately diagnose and treat skin cancers, improving patient outcomes and lessening the burden of this illness. Additional research and validations might be required to guarantee the model's robustness across various datasets and actual clinical settings.

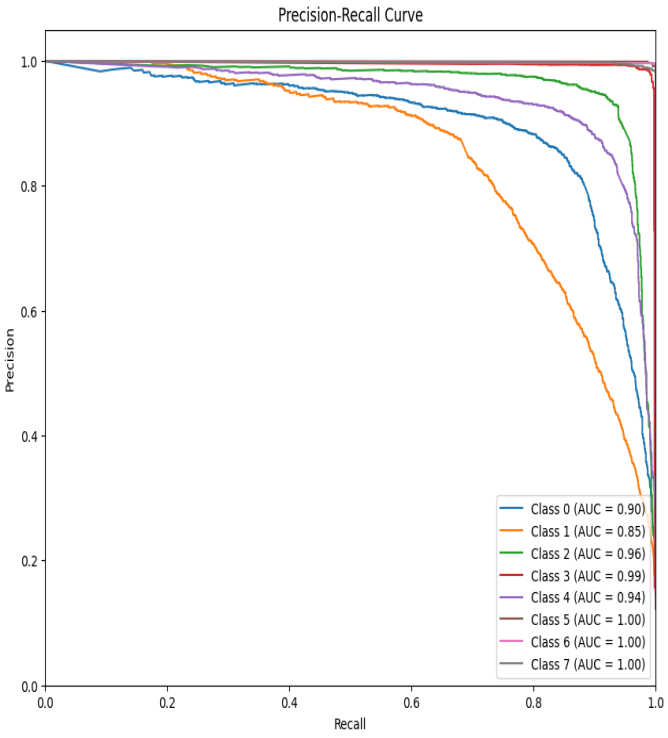

Fig. 4 Proposed method Precision-recall graph on ISIC-2019dataset

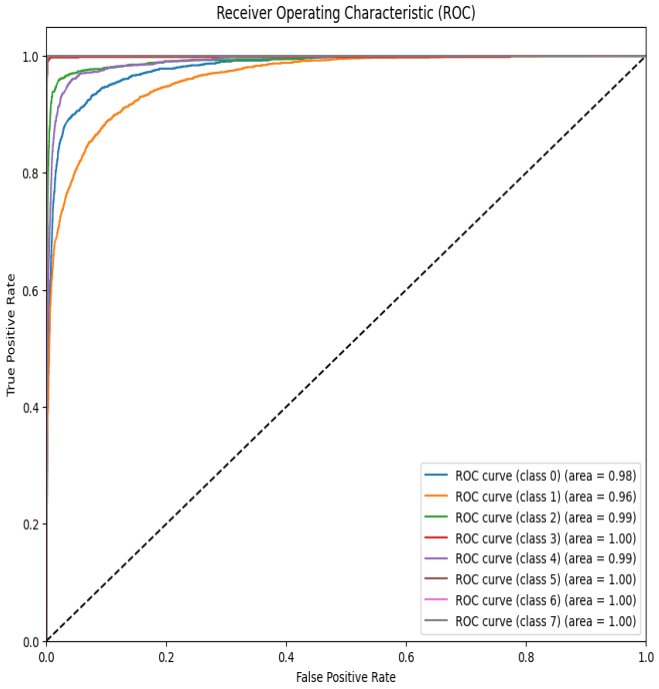

Fig 5 Proposed method Receiver operating Characteristics (ROC) graph on ISIC-2019 dataset

A binary classification model's effectiveness is revealed by the values for each class's AUC-PR (Area Under the Precision-Recall Curve). These numbers show how well the model balances recall and precision. AUC-PR values of class codes 0, 1, 2, 3, 4, 5, 6, and 7 are 0.90, 0.85, 0.96, 0.99, 0.94, 1.00, 1.00, and 1.00, respectively, among the classes, indicate varying levels of efficacy. The class with an AUCPR of 1.00, which denotes excellent precision-recall tradeoff and guarantees both high precision and recall, is particularly noteworthy. Overall, these AUC-PR values highlight the model's exceptional performance in some classes with a perfect precision-recall balance, as well as its ability to successfully distinguish between various classes. The receiver operating characteristics graph of the proposed model on ISIC 2019 dataset is shown in Fig 5.

Fig 6 Proposed method training and validation accuracy and training and validation loss graph on ISIC-2019 dataset

The training accuracy and validation accuracy and training loss and validation loss graph of the proposed model on ISIC-2019 dataset is shown in Fig 6 Proposed method training and validation accuracy and training and validation loss graph on ISIC-2019 dataset. The comparison of the proposed method performance with state-of-the-art methods on ISIC-2019 datasets is shown in Table 4.

Table 4 Comparison of the proposed method performance with previous methods on ISIC-2019 datasets

Model used	Accuracy (%)	Precision (%)	Recall	F1-score
Specific DCNN(CSLNet) [27]	89.58	90.66	89.58	89.75
Inception Net in GoogleNet [30]	91.89	-	90.00	-
Spiking VGG-13 [26]	89.57	-	-	90.07
Transfer learning GoogleNet, ResNet-101, and NasNetLarge [31]	88.33	-	88.46	
Proposed model	92.0	92.12	92.37	92.0

The proposed model outperforms current approaches in classifying skin cancer. It distinguishes itself as a more trustworthy tool for skin cancer diagnosis with an accuracy of 92.0%, beating Specific DCNN (CSL-Net) [27] at 89.58%, Inception Net in Google-net [30] at 91.89%, and Spiking VGG-13 [26] at 89.57%. The model also surpasses Specific DCNN's [27] recall of 92.37% and Inception Net in Google net's [30] recall of 90.00%, demonstrating its effectiveness in identifying real positive cases and reducing the risk of false negatives.

Furthermore, the proposed model achieves a harmonious balance between precision and recall with a balanced F1-score of 92.0%, reaffirming its status as a reliable option for skin cancer classification. Overall, it provides better accuracy, precision, recall, and F1-score, improving its reliability and accuracy in skin cancer detection and classification, especially for early
diagnosis and better patient care.

4. DISCUSSION

Skin cancer is an important cause of worry everywhere, and early and accurate detection are essential for effective treatment. The YOLO NAS (You Only Look Once Neural Architecture Search) based convolutional network is one such method used for skin cancer classification. Convolutional neural networks (CNNs) have shown their potential in medical image analysis. The classification results demonstrate how well this method identifies various skin cancer types.

The precision-recall table's classification results show how well the YOLO NAS-based convolutional network performs for various subtypes of skin cancer. Key metrics for assessing classification models include precision, recall, and F1-score.

5. CONCLUSION

Overall, the skin cancer classification method presented in this study, which utilises a YOLO-NAS based Convolutional network, has shown impressive performance in terms of different evaluation metrics. The effectiveness of the method in accurately identifying and classifying various skin lesions is highlighted by the balance between precision and recall, as indicated by strong values for both. The model's accuracy in predicting positive outcomes is evident from the high precision scores achieved for most classes. The results consistently match the model's impressive overall accuracy of 92%, confirming its ability to effectively classify instances across the dataset.

Furthermore, the F1-scores obtained provide additional evidence of the framework's balanced performance in terms of both recall and precision, increasing confidence in its potential for diagnosis. This framework makes a noteworthy contribution to the field by providing a customised approach using a YOLO-NAS based Convolutional network. The proposed methodology is distinguished by its innovative approach of customising the focal loss function for the ISIC-2019 dataset, giving priority to challenging samples.

In the future, there are promising opportunities for further research and improvement. Potential directions to improve both the accuracy and efficiency of the framework include further optimising architectural choices, exploring multi-scale feature fusion techniques and developing real-time deployment strategies. Overall, this study establishes the groundwork for a crucial tool that shows potential in assisting healthcare practitioners in the timely detection and diagnosis of skin cancer conditions, making notable contributions to progress in the field.

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