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Efficient Deep Learning Approach for Modern Skin Cancer Detection

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Abstract

Objective: The objective of this study is to develop an efficient deep learning approach for the accurate detection of skin cancer in modern healthcare settings. Skin cancer is a prevalent and potentially life-threatening disease, and early detection plays a crucial role in improving patient outcomes. Traditional methods for skin cancer detection often suffer from limited accuracy and efficiency, highlighting the need for advanced techniques that can effectively analyze medical images and provide reliable diagnoses. **Methods:** In this research, we propose an innovative deep learning approach that is whale-optimization based on convolutional neural networks (CNNs) to achieve efficient and accurate skin cancer detection. We leverage a large dataset of annotated skin images to train our model, allowing it to learn discriminative features associated with different types of skin lesions. Transfer learning enables the utilization of pre-trained models on large-scale image datasets, enhancing the performance of our approach even with limited labeled data. **Results:** Our experimental results demonstrate the effectiveness of our proposed deep learning approach for skin cancer detection. The model achieves high accuracy in distinguishing between malignant and benign skin lesions, outperforming traditional methods and showcasing its potential as a valuable tool for dermatologists and healthcare professionals. The efficient design of our approach enables real-time analysis of skin images, facilitating timely and accurate diagnosis. **Novelty:** In the initial convolution layer, a 7x7 filter is employed, and then the max-pooling layer is applied. The dense block consists of a convolution layer with filter sizes of 11 and 33, which is added to the max-pooling layer following the dense block. This design has four dense blocks, to which are added convolution blocks for each block and a transition layer. After the last dense block, a 77 filter is applied for the global average pooling layer of CNN, which follows the fully connected layer. The architecture of ResNet bypasses a few ResNet connections in order to establish the direction relationship. The ResNet makes use of bottleneck blocks, which are employed to decrease a parameter.

Keywords: Deep Learning; Convolutional Neural Network; Skin Cancer; Whale Optimization; ResNet; DenseNet; Inception

1 Introduction

Skin cancer is a prevalent and potentially life-threatening disease, with increasing incidence rates worldwide[1]. Timely and accurate detection of skin cancer plays a crucial role in improving patient outcomes and reducing mortality rates[2]. Traditional methods for skin cancer detection heavily rely on visual inspection by dermatologists, which can be subjective and prone to errors. With the advancements in digital imaging technology and the availability of large datasets, there is an opportunity to leverage machine learning techniques to develop more efficient and accurate skin cancer detection systems.

Deep learning, a subset of machine learning, has gained significant attention in the medical field due to its ability to automatically learn intricate patterns and features from large-scale datasets. Convolutional neural networks (CNNs), a popular type of deep learning model, have demonstrated remarkable success in image recognition tasks, including skin cancer detection. By training CNNs on annotated skin images, these models can learn to differentiate between benign and malignant skin lesions with high accuracy.

In this study, we aim to develop an efficient deep learning approach for modern skin cancer detection. Our approach utilizes convolutional neural networks and transfer learning to enhance the accuracy and efficiency of the detection process. Transfer learning allows us to leverage pre-trained models on large-scale image datasets, enabling the extraction of relevant features from skin images even with limited labeled data. By combining the power of deep learning and transfer learning, we seek to overcome the limitations of traditional methods and provide a more robust solution for skin cancer detection.

The main objective of this research is to investigate the effectiveness of our proposed deep learning approach in accurately detecting various types of skin lesions and distinguishing between malignant and benign cases. We will evaluate the performance of our model using a comprehensive dataset of annotated skin images and compare it with existing methods to demonstrate its superiority. Additionally, we will assess the efficiency of our approach by examining its processing speed and computational requirements, ensuring its practical applicability in real-time clinical settings.

The outcomes of this research have the potential to significantly impact the field of dermatology and improve patient care. An efficient deep learning approach for skin cancer detection can aid dermatologists in making more accurate diagnoses, leading to early intervention and improved treatment outcomes. By automating the detection process, the workload of healthcare professionals can be reduced, allowing them to focus more on patient care. Furthermore, our research contributes to the growing body of knowledge in the application of deep learning techniques for medical image analysis, paving the way for further advancements in the field of computer-aided diagnosis for skin cancer.

2 Related Work

Compared to conventional statistical methods, the artificial neural network (ANN) is a powerful technology. In terms of results, they are more accurate than data regression models. The ANN is a framework for distributed data processing. Each processing unit is linked to neurons through a single output connection. The information is entirely kept in the internal memory of the CPU unit. The correct diagnosis of diseases is a fundamental responsibility of medical science. Artificial neural networks are the most widely utilised and successful soft computing tool for diagnostics (ANN). Due of their aptitude for learning and acquiring information, they play a vital role in taxonomy. These signals are processed inside the neuronal cell body before being sent to neighbouring neurons through the output axon and terminals. Cancer has prompted a frenzy of research as the number of those affected with the disease rises year. Enhancements will be made to software systems for detecting and analysing Epiluminescence microscopy pictures of patients' skin patches [3].

Several layers of neural networks were used to construct a deep convolutional neural network (DCNN). Convolutional and pooling layers include many layers. These layers were used to extract attributes from the input colour skin photographs. The last stage layer of a fully linked layer forecasts classes using the received class score. The DCNN may be applied with unique labelled data that is distinct from the training data. Due to a paucity of labelled data, noise, and anomalies, the application of DCNN in the classification of skin lesions was restricted. Dermoscopy photos of the same feature may reveal substantial variation, but lesions of different sorts may look virtually similar. All of these difficulties motivated the recommended classification system for skin lesions [4].

CNN is highly adept at addressing complex problems. CNN's Convolution layer has a high number of weights, which the pooling layer subsamples to give the convolution layer's output while reducing the data ratio of the layer below. Ultimately, the result of the pooling layer is leveraged to pump data into the fully linked layer. CNN's convolution layer is necessary for a variety of information applications, including numerous 2D matrices and classification. There is no standard method for estimating inputs and outputs since there is none [5]. Deep convolutional neural networks (CNNs) are a revolutionary kind of artificial neural network that yields great results for a variety of image processing tasks. In recent years, DNN has been employed for medical imaging in a variety of methods. Deep neural networks were used to classify melanomas at the dermatologist level [6]. CNN was used to classify melanoma using a single CNN that was directly trained end-to-end from pictures. The method's effectiveness was proved to 21 board-certified dermatologists using clinical photographs that had been confirmed by biopsy. Convolutional neural networks (CNNs) surpassed previous algorithms and quickly became the industry standard for classifying skin cancers. By automatically recognising high-level abstractions from datasets, CNN improved classification accuracy and freed machine learning professionals of the chore of "feature engineering." The present work focuses on transfer learning, a method that permits a model trained for one task to be partly reused for another [7].

GoogLeNet was used in the detection and classification tasks of the ImageNet Large Scale Visual Recognition Challenge (ILSVRC). The depth of the network, which consists of 22 layers, distinguishes it from AlexNet, the first classification network. In addition, they added extra neurons to increase the network's complexity. It is comprised of Inception components, including max pooling and convolution layers, with ReLU activation. The input is a 224 x 224 RGB picture and the output is a probability vector with 1000 classes [8]. InceptionV3 is an enhanced version of the original Inception, with 33 convolution kernels replacing 77 kernels and more convolutions added. In addition, as the network grew substantially, the filter size in inception modules decreased by half. This version of Inception has more modules than its predecessor. The network consists of 42 layers and is 2.5 times as costly to compute as GoogleNet. The validation set for the ILSVRC 2012 challenge demonstrated a substantial improvement over the existing technique [9].

CNNs are capable of classifying dermatological lesions. The feature extractor is produced by training a CNN model on a massive dataset. This situation employs another classifier, such as k-nearest neighbours, artificial neural networks, and support vector machines. CNNs may employ end-to-end learning to comprehend the relationship between raw pixel data and class labels. In contrast to the conventional workflow for machine learning, feature extraction is now seen as an essential part of categorization rather than a discrete, independent processing step. The linear classification employing a feature obtained from a pre-trained CNN on a dataset of 1300 natural pictures was shown to be more accurate at differentiating up to ten skin lesions. In the suggested method, there is no lesion segmentation or costly preprocessing. Over five and ten courses, the accuracy of this approach was 85.8\% and 81.9\%, respectively. However, the number of images utilised for training in this research was insufficient to extract relevant characteristics from the data [10,11]. For the categorization of skin lesions, many approaches for constructing DNNs with various hyper-parameters and variable input processing have been given. Ensemble may be used to mix not just numerous machine learning models but also alternate hyperparameter selections for these models. In comparison to seven classes, the Xception model has a 90 percent accuracy in the ISIC2018 and ISIC2017 datasets [12].

Balaha and Hassan [13] proposed a deep transfer learning and sparrow search algorithm for skin cancer detection, classification, and segmentation. The model could achieve 85.87\% by the MobileNetV2 pre-trained model. Using the HAM10K dataset, they achieved 98.83\% accuracy. Thanka *et al.* [14] proposed a hybrid approach for melanoma detectiion and classification. The hybrid model included VGG16 and XGBoost, and achieved 99.1\% in terms of accuracy. Mazhar *et al.* [15] highlighted the role of Machine Learning and Deep Learning Approaches for the Detection of Skin Cancer in depth. Though the findings are useful, there are no significant contribution that add in the detection of skin cancer. Dildar *et al.* [16] review Skin Cancer Detection Techniques that were based on Deep Learning. Though the findings may be useful, there are no significant contribution that add in the detection of skin cancer. Similarly, Wu *et al.*[17] wrote a systematic review on Skin Cancer Classification with Deep Learning, but there is no significant contribution that add in the detection of skin cancer.

3 Methodology

3.1 Convolutional Neural Network

Deep learning is the most effective technology for analysing medical images. Deep learning improves detection success rates as a result of CNN's emphasis on hierarchical representation. It can extract attributes since no previous information is required. Due to its advantages, an automated diagnostic tool was developed to enable non-specialists to design the structure of CNN without previous knowledge of the subject. The deep learning structure consists of hidden layers that enable the abstraction of features. Figure 1 reveals the hidden layer of the deep learning network, which is briefly detailed below.

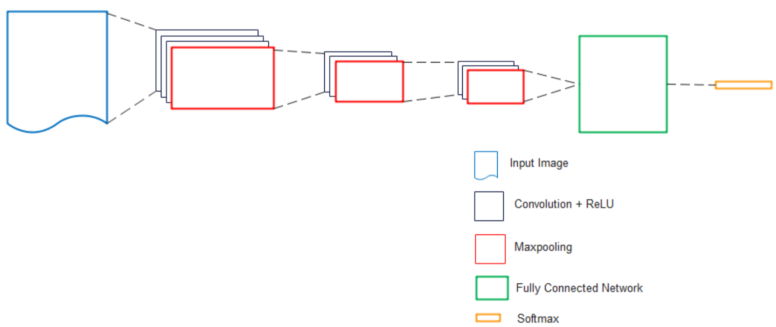

Fig 1. Architecture of proposed Convolutional Neural Network

3.2 Inception-V3 Classification

The Inception-v3 network is an improved version of the well-known GoogLeNet network, which has exhibited good classification performance in several biological applications using transfer learning. Similar to GoogleNet, Inception-v3 created an inception model that combines many convolutional filters of varying sizes into a single filter. This method reduces the number of parameters that must be taught and the complexity of calculations[18]. Figure 2 depicts the Inception-v3 DCNN fundamental model.

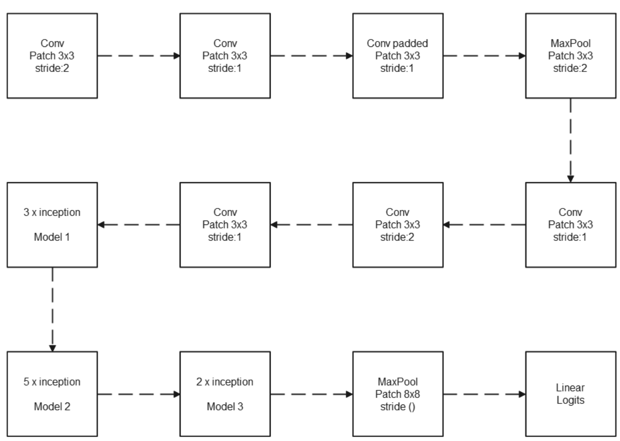

Fig 2. Inception-V3 Architecture

The DCNN model Inception-V3 is both complex and profound. Approximately 25 million parameters and 5 billion multiply-add floating-point operations are used to classify each picture. To successfully train such a big network, you will need a lot of data, a lot of time, and a lot of GPUs, which are often out of reach for a single person. Consequently, a method known as transfer-learning is used, which enables us to employ the weights of a previously-trained network while reducing training time and computing complexity. The Inception V3 model was pre-trained with over 1 million pictures from 1,000 discrete categories.

The design of Inception-deep v3, which consists of multiple types of filters, enables the automatic extraction of difficult ordered characteristics from an image, resulting in significantly improved classification performance in computer vision applications compared to manually-executed feature extraction. The Inception-v3 network is a huge system, including about 25 million parameters and 5 billion multiply-add and floating-point operations. As a result, the transfer learning technique for training the network is investigated, which enables us to employ the weights of a previously trained network while reducing training time and difficulty. After being trained with almost one million photos, the trained InceptionV3 system attained an advanced level of accuracy in recognising 1000 classes of generic objects. The Inception-v3 has 315 layers, the first 41 of which are permanently frozen to avoid weight fluctuations. The remaining layers were retrained using photos of skin, enabling CNN-softmax to extract high-level relevant properties. The average-pool, softmax classifier, fully-connected layer, and output layer of the network were removed, leaving just the remaining layers to extract skin image attributes.

3.3 ResNet

Figure 3 depicts the architecture of ResNet. It bypasses the few ResNet connections in order to establish the direction relationship. The ResNet makes use of bottleneck blocks, which are employed to decrease a parameter. ResNet is formulated mathematically as follows in Equation (1):

$$Y = R\left(\delta_{Loc}, \left(W_i\right\}\right) + \delta_{Loc} \tag{1}$$

The output vector is designated by the letter Y. The learnt residual mapping is indicated by R(...). The input and output dimensions are the same.

The architecture of ResNet included convolutional blocks. The first layer of convolution is represented by the first block. Each of the three building elements shown in the second layer contains three convolution layers. There are four building pieces in the third convolution layer. Fourth and fifth convolution layers have 23 and 3 construction components, respectively.

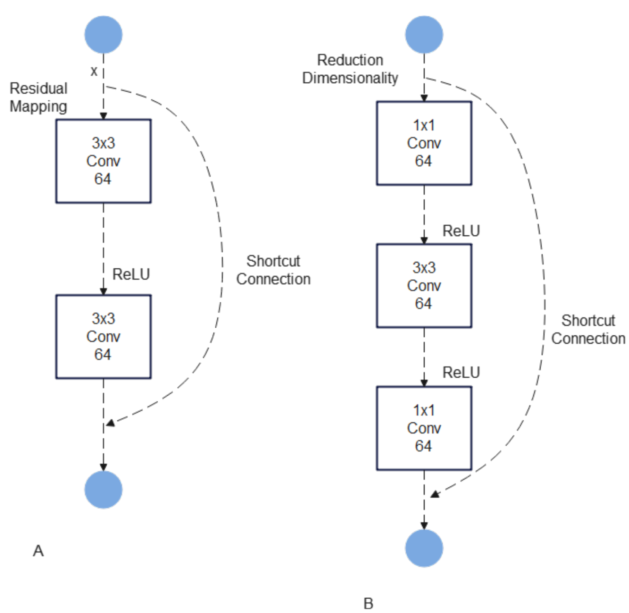

Fig 3. ResNet Architecture

3.4 DenseNet

All defining characteristics of the DenseNet architecture are listed sequentially. The DenseNet mathematically represents the process of concatenation as follows in Equation (2) :

$$Z_L = \varphi_L\left((Z_0, Z_1, Z_2, \ldots, Z_{L-1}]\right) \tag{2}$$

φ_L nonlinear transform that is a ReLU composite function. The convolution procedure is used to refer to Layer $L-1$'s concatenation feature.

Figure 4 depicts DenseNet's architectural layout. In the initial convolution layer, a 7x7 filter is employed, and then the max-pooling layer is applied. The dense block consists of a convolution layer with filter sizes of 11 and 33, which is added to the max-pooling layer following the dense block. This design has four dense blocks, to which are added convolution blocks for each block and a transition layer. After the last dense block, a 77 filter is applied for the global average pooling layer of CNN, which follows the fully connected layer.

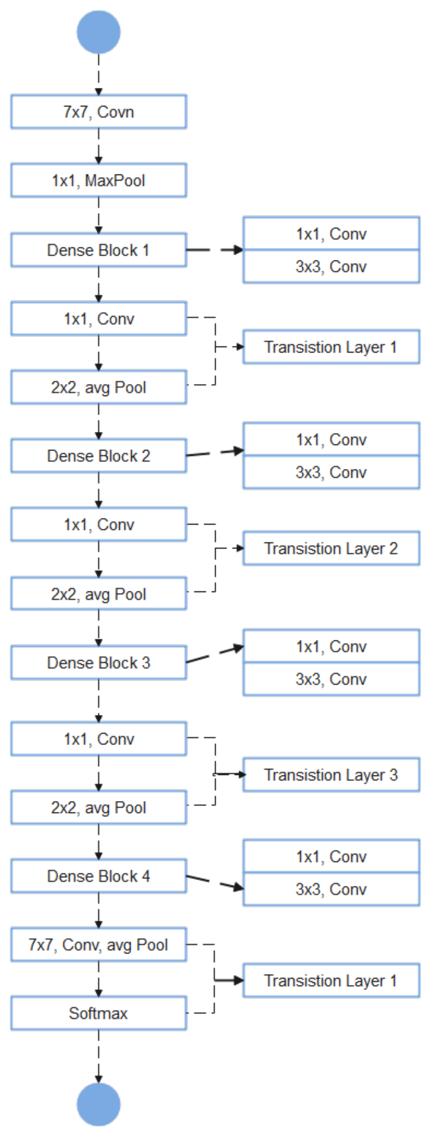

Fig 4. DenseNet Architecture

3.5 Whale Optimization Algorithm

A mathematical model of a humpback whale is developed to reproduce the prediction approach using the intelligence optimization methodology called as whale optimization algorithm. The prediction procedure is divided into two parts inside the whale optimization method. Exploitation is the first step, which consists of a spiral bubble-based network attack, and exploration is the second phase, which consists of random victim hunting. Figure 5 displays the structure of the suggested whale optimization approach.

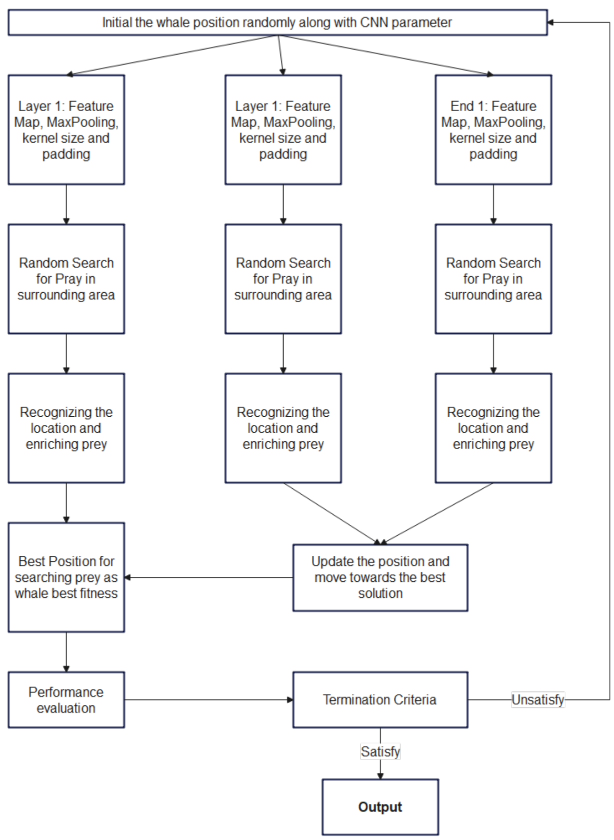

Fig 5. Whale Optimization

The whale optimization approach utilises whale number N, domain problem dimension k, and whale position at iteration l as Equation (3) and Equation (4).

$$X_m(k) = \left(X_m^1, X_m^2, X_m^3, \ldots, X_m^d\right) m \tag{3}$$

$$X_m(k) = 1,\ 2,\ 3,\ \ldots,\ N.X^*(l) \tag{4}$$

During the first phase, the surrounding mechanism shrinks and updates the twisting position, and the shrinking mechanism delivers the location update, which is expressed using the formula in Equation (5).

$$X(l+1) = X*(l) - A.(C \times X*(l) - X(l)| \tag{5}$$

The current position is $X(l)$, and the updated position is $X(l+1)$. $|\ldots|$ is the absolute value, which is the product of absoluter values.

$$A = 2c.r - c \tag{6}$$

$$C = 2.r \tag{7}$$

From the Equation (6) and Equation (7), r represents a random integer between 0 and 1. c represents Convergence factor. The value declines linearly from c_1 to c_2 as the number of rounds increases as in Equation (8) and Equation (9).

$$c_1 = 2 - 2 \times \frac{l}{L} \tag{8}$$

$$c_2 = -1 - \frac{l}{L} \tag{9}$$

The position updating strategy is depicted in Equations (10) and (11) and Equation (12):

$$X(l+1) = D.e^{dn} cos(2\pi n) + X(l) \tag{10}$$

where D represents the distance between the whale and the optimal value.

$$D = (X * (l) - X(l)| \tag{11}$$

where d represents spiral shape

$$l = c_2 * rad + 1 \tag{12}$$

The process of updating the encircling shirking and spiral position is complemented by the whale prediction. The probability of downsizing and job adjustment is roughly 0.50. The mathematical model is written in Equation (13) as follows:

$$X(l+1) = \begin{cases} X * (l) - A.\,|C \times X * (l) \langle 0.5 \\ D.e^{dn}\cos(2\pi n)\ +\ \mathrm{X(l)m} \leq 0.5 \end{cases} \tag{13}$$

The random search approach is presented in Equation (14) and Equation (15) as follows:

$$X(l+1) = X_{rand} - A.D^1 \tag{14}$$

$$D^1 = (C.X_{rand} - X| \tag{15}$$

X_{rand} represents the selected position randomly. Whereas, X represents the current position.

4 Results and Discussion

The HAM10000 (HAM10K) dataset with 1103 images is used in the research to validate skin cancer. The deep model is analysed using the inception V3, ResNet, and DenseNet model to classify skin cancer into its several groups, including Melanocytic nevi, Basal cell carcinoma, Benign keratosis, Actinic keratosis, Melanoma, Dermatofibroma, and Vascular Lesions. Fifty percent of the samples have been verified by histopathology, and the truth of the other samples is now being determined. The data source contains many images of lesions that may exist inside the HAM10000, as specified by the lesion id column. Figure 6 provides a visual representation of the data's statistics.

It is observed that the majority of the HAM10000 dataset consists of images of the same kind of skin cancer.

Table 1 illustrated the training loss and precision of the proposed CNN architecture. Whereas, Table 2 clearly demonstrates that the proposed DenseNet architecture provides the greatest accuracy and lowest loss compared to other models.

Figure 7 compares the recommended whale-optimized CNN approach with the standard CNN technique for identifying and classifying skin cancer using the HAM10000 dataset.

Table 3 displays the results of different studies on skin lesion classification using various datasets and models. The accuracy and loss metrics are reported for each combination. It can be observed that the HAM10K dataset stands out as the only unlabeled dataset, whereas the other datasets are labeled. The presence of labeled data in the other datasets contributes to higher accuracy rates achieved with the respective models.

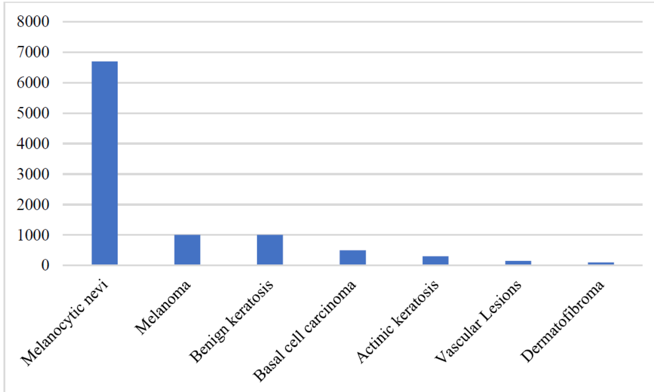

Fig 6. Classes Frequency in the dataset

Table 1. Performance metric with HAM1000 dataset

Architecture	Accuracy	Precision	Sensitivity	Specificity
Inception V3	0.81	0.83	0.84	0.84
ResNet	0.82	0.82	0.85	0.81
DenseNet	0.89	0.8	0.85	0.83

Table 2. Performance metrix: CNN Model

Architecture	Training	Testing	Validation
Inception V3	0.92	0.87	0.85
ResNet	0.93	0.83	0.89
DenseNet	0.96	0.89	0.92

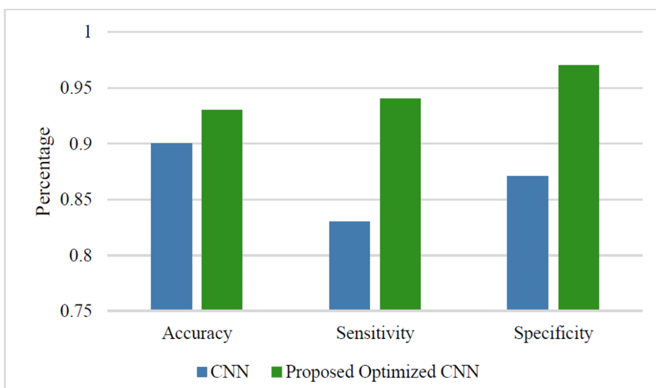

Fig 7. Comparison of optimized CNN with traditional CNN model

Table 3. Studies with HAM10K and Others Datasets Result Comparison

Author	Dataset	Model	Accuracy	Loss
Mahbod *et al.*	ISIC 2017	CNN	87.7	*
Khan *et al.*	ISBI2016	DenseNet201	94.50%	5.6
	ISBI2017		93.40%	6.6
Balaha and Hassain	HAM10k	CNN	85.87%	4.99
Thanka *et al.*	ISIC	VGG16+LightBGM	99.10%	*
		VGG16+XGBOOST	97.20%	*
This study	HAM10K	CNN	92.00%	8.3

5 Conclusion

As skin cancer occurrence rates have increased over the last several decades, there is an ongoing need to address this global public health risk. Deep learning applications are the optimal option for all contemporary detection methods. The exceptional performance of Deep CNNs in medical image classification led to its concurrent use in skin cancer classification. Despite the fact that several studies for the classification of skin cancer have been undertaken in the past, they have failed to broaden their study to include the most prevalent classifications of skin cancer. In this research, the approach of deep learning is suggested for categorising the various types of skin cancer. The classification performance of a CNN with three ensemble models that has been pre-trained is anticipated. The whale optimization improves the system's precision. The suggested DenseNet performs better than an alternative ensemble model. The ensemble model improves the accuracy of skin cancer classification but has no significant role in the performance enhancement of the deep learning approach. In future, we would like to implement hybrid modeling for Cancer detection, also that run on minimal system configuration. We would like to explorer with several publicly available datasets and compare with the real-world problem.

6 Declaration

Presented in 4th Mizoram Science Congress (MSC 2022) during 20th & 21st October 2022, organized by Mizoram Science, Technology and Innovation Council (MISTIC), Directorate of Science and Technology (DST) Mizoram, Govt. of Mizoram in collaboration with science NGOs in Mizoram such as Mizo Academy of Sciences (MAS), Mizoram Science Society (MSS), Science Teachers' Association, Mizoram (STAM), Geological Society of Mizoram (GSM), Mizoram Mathematics Society (MMS), Biodiversity and Nature ConservationNetwork (BIOCONE) and Mizoram Information & Technology Society (MITS). The Organizers claim the peer review responsibility.

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